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PROBABILISTIC NEURAL NETWORKS FOR GAS TURBINE FAULT RECOGNITION

Fault identification algorithms based on measured gas path variables constitute an important component of a gas turbine engine condition monitoring system. In addition to gas path faults diagnosis, these algorithms are capable to identify malfunctions of sensors and an engine control system. The fault identification algorithms widely use pattern recognition techniques, in particular, different artificial neural networks. Since monitoring system efficiency depends on accuracy of all system's components, the most exact mathematical technique should be chosen for every component. To recognize gas turbine faults, a specific network type, multilayer perceptron (MLP), is mostly applied. However, other network type, probabilistic neural network (PNN), can be applied as well. It uses a probabilistic measure to recognize the faults. In the present paper, the PNN is firstly tailored to a gas turbine diagnosis application and then compared with the MLP. The comparison has shown that both networks yield practically equal accuracy. The PNN is recommended for real gas turbine monitoring systems because, in addition to a diagnostic decision, this network provides confidence estimation for this decision.

Key words: *gas turbine, fault identification, pattern recognition, probabilistic neural network, multilayer perceptron.*

Introduction

To keep high reliability of gas turbines and reduce maintenance costs, many monitoring and diagnosis systems have recently been developed. Benefits from their application above all depend on the accuracy of diagnostic algorithms constituting the system.

Gas turbine fault identification algorithms based on measured gas path variables (temperature, pressure, rotation speed, fuel consumption, etc.) present an important monitoring system component. With the gas path variables not only gas path abrupt faults and gradual deterioration mechanisms [1] are diagnosed, but also sensor faults [2, 3] and control system malfunctions [4] can be identified. The fault identification algorithms widely use the pattern recognition theory. In the last three decades, the use of many recognition techniques has been reported: first of all, Artificial Neural Networks [5-9], but also Bayesian Approach [5, 6], Support Vector Machines [7], Genetic Algorithms [10], and Correspondence and Discrimination Analysis [11].

The neural networks present a fast growing technique for gas turbine diagnostics. Among the neural networks, the Multilayer Perceptron (MLP) is the most frequently used technique [9]. Nevertheless, other network type, Probabilistic Neural Network (PNN), is also applied to diagnose gas turbines [3, 12, 13]. It recognizes (classifies) the faults using the criterion of fault probability. In this way, the PNN has an advantage that every diagnostic decision is accompanied with a probabilistic confidence measure.

The present paper tests the PNN and compares it with the MLP in order to choose the best technique for real gas turbine monitoring systems. To the end of comparison, both networks were included into a special testing procedure. It simulates numerous cycles of the diagnosis and computes for each network an averaged probability of a correct diagnosis (true positive rate). The procedure is realized in Matlab (MathWorks, Inc), which includes a neural networks toolbox that simplifies network creation, training, and use. The procedure was adapted and the calculations of network comparison were made for an industrial gas turbine intended for driving a centrifugal compressor.

The paper is structured as follows. The compared networks are described in Section 1. Next, Section 2 outlines the approach to fault recognition and network comparison realized in the testing procedure. Comparison conditions are then specified in Section 3. Finally, Section 4 presents comparison results.

1. Networks compared

Foundations of the compared networks, MLP and PNN, can be found in many books on recognition theory or neural networks, for example, in [14]. The next two subsections give only a brief network description, which is necessary for better understanding the present paper.

1.1. Multilayer perceptron

The MLP is intended for solving both approximation and recognition (classification) problems. It is a feed-forward network in which signals propagate from its input to the output with no feedback. The structural scheme given in Fig.1 helps to better explain perceptron operation.

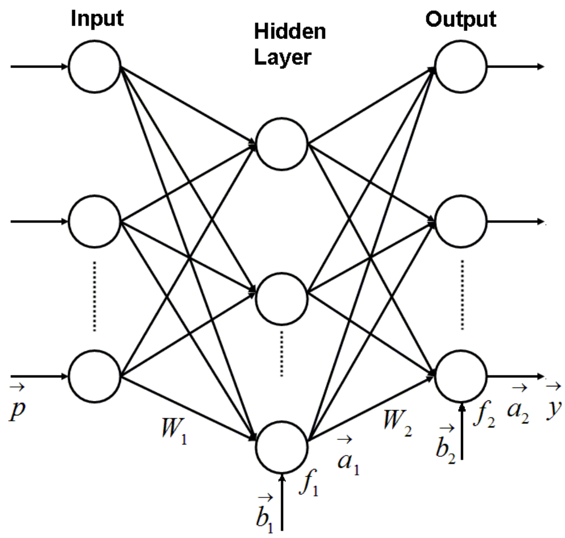

Fig. 1. Multilayer perceptron

The input of each hidden layer neuron is the sum of perceptron inputs (elements of a pattern vector $\vec{p}$) multiplied by the corresponding coefficients of a weight matrix W_1 with a bias (element of a vector $\vec{b}_1$) added. This neuron input is transformed by a hidden layer transfer function f_1 into a neuron output (element of a vector $\vec{a}_1$). Such computation is reiterated for all hidden layer neurons. The perceptron output layer operates in the same way considering the vector $\vec{a}_1$ as an input vector. Thus, a network output vector can be given by the expression $\vec{y} = \vec{a}_2 = f_2\{W_2 f_1(W_1\vec{p} + \vec{b}_1) + \vec{b}_2\}$. When the perceptron is applied to a classification problem, each output y_k gives a closeness measure between the input pattern $\vec{p}$ and a class D_k. The pattern is usually assigned to the closest class and such classification can be considered deterministic.

During the learning, unknown perceptron's quantities W_1, $\vec{b}_1$, W_2 and $\vec{b}_2$ are generally determined by a back-propagation algorithm, in which the network output error is propagated backwards to correct these quantities. They change in the direction that provides error reduction unless the learning process converges to a global error minimum. The back-propagation algorithm needs the transfer functions to be differentiable and usually they are of a sigmoid type.

The other network analyzed in the present paper is a probabilistic neural network (PNN). It differs from the MLP by the application, structure, and the transfer functions employed.

1.2. Probabilistic neural network

The PNN is intended for classification problems. It is a specific type of networks based on radial basis functions. The scheme in Fig. 2 illustrates probabilistic network's operation. Like the perceptron, this network consists of two layers.

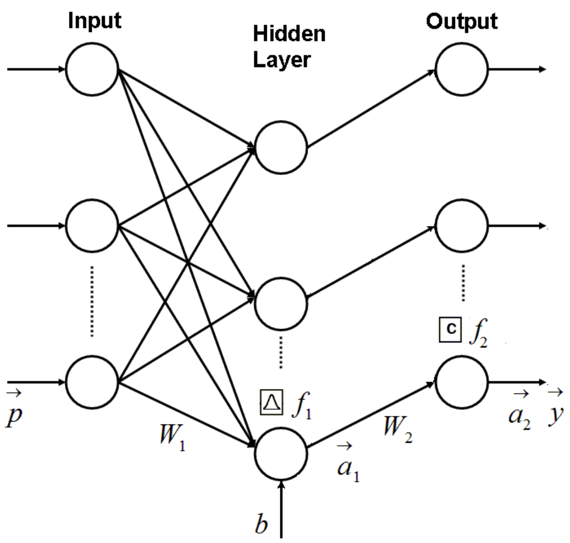

Fig. 2. Probabilistic neural network

The hidden layer (a.k.a. radial basis layer) is quite different from the perceptron's layers. It is formed in the basis of learning patterns united in a matrix $\mathbf{W_1}$. Each learning pattern $\vec{w}_{1j}$ specifies a center of a radial basis function (RBF) of one hidden neuron therefore a hidden layer dimension equals a total number of the learning patterns. A neuron input L_j is firstly computed as a Euclidean distance between the function center $\vec{w}_{1j}$ and an input pattern $\vec{p}$. A hidden neuron output a_j is then calculated through the radial basis function f_{1j} resulting in $a_j = f_{1j} = e^{-\frac{L_j^2}{B^2}}$. The parameter B called a spread determines an action area of the RBFs. The closer the input vector is situated to the neuron center, the greater the neuron output will be. These outputs, elements of a hidden layer output vector $\vec{a}_1$, indicate how close the input vector is to the learning patterns.

For each class the corresponding neuron of the output layer sums the signals a_j related with the learning patterns of the same class. To this end, a matrix W_2 is composed in a particular way from 0- and 1-elements. A product $W_2 \vec{a}_1$ is then computed resulting in a vector of probabilities of the considered classes. Finally, the output layer transfer function f_2 produces a 1 corresponding to the largest probability, and 0's for the other network outputs. Thus, the PNN classifies the input vector $\vec{p}$ into a specific class because of its highest probability. Given that this network makes probabilistic rather than deterministic decisions, such classifying is closer to reality than the perceptron-based classifying.

2. Procedure to test and compare the networks

The network testing procedure mentioned in the introduction embraces all the stages of gas turbine fault classification, namely, feature extraction, construction of fault classes, classifying an actual fault pattern, and estimation of classification accuracy. They are briefly described below.

Feature extraction. Some measured variables set a gas turbine operation point and are united in a vector of operating conditions $\vec{U}$. The rest of measured gas path variables are available for engine condition monitoring and form an $(m\times 1)$-vector of monitored variables $\vec{Y}$. Since they much more depend on the operating point than on engine health, not variables themselves but their deviations from an engine baseline $\vec{Y}_0$ are fault features to be monitored. In the present study, the faults are simulated and m features

$$Z_i = \left(\frac{Y_i(\vec{U}, \vec{\Theta}_0 + \Delta\vec{\Theta}) - Y_{0i}(\vec{U}, \vec{\Theta}_0)}{Y_{0i}(\vec{U}, \vec{\Theta}_0)} + \varepsilon_i \right) \Big/ a_i \quad (1)$$

are computed through a gas turbine thermodynamic model

$$\vec{Y}(\vec{U}, \vec{\Theta}). \quad (2)$$

The model computes the monitored variables as a nonlinear function of steady state operating conditions and engine health parameters $\vec{\Theta} = \vec{\Theta}_0 + \Delta\vec{\Theta}$. Nominal values $\vec{\Theta}_0$ correspond to a healthy engine whereas changes $\Delta\vec{\Theta}$ called fault parameters slightly shift performance maps of engine modules (compressors, combustor, turbines, etc.) allowing fault simulation. A random error ε_i makes the deviation more realistic and a parameter a_i normalizes the errors of different deviations simplifying fault class description. The deviations given by expression (1) constitute an $(m\times 1)$-vector $\vec{Z}$, which is a pattern to be classified.

Construction of fault classes. For the purposes of diagnosis, numerous gas turbine faults are divided into a limited number q of classes $D_1, D_2, ..., D_q$. Each class corresponds to one engine module and is described by its fault parameters $\Delta\Theta_j$, flow parameter and efficiency parameter. Two class types are considered: a class of singular faults is constructed by changing one fault parameter while for a class of multiple faults two parameters of the same module are varied independently. For each class, singular or multiple, numerous patterns $\vec{Z}$ are generated according to expression (1) setting the necessary quantities $\Delta\Theta_j$ and ε_i by the uniform and Gaussian distributions accordingly. A totality **Z1** of all classification's patterns is employed to train the used neural network and is therefore called a learning set.

Classifying fault patterns. In addition to the observed pattern $\vec{Z}$ and the constructed fault classification **Z1**, a neural network (MLP or PNN) for classifying fault patterns is an integral part of a whole gas turbine diagnostic algorithm. Unknown network coefficients are determined with data of the learning set **Z1** as described in Section 1. Once the coefficients have been determined, the network is ready for use, but before real network application it is important to estimate network's classification accuracy.

Estimation of classification accuracy. To test and validate the network, an additional data sample **Z2** called a validation set is created in the same way as the set **Z1**. The only difference is that other random numbers are generated within the same distributions. The network classifies each pattern of the set **Z2**, producing the diagnosis d_l. Comparing d_l with a known class D_j for all validation set patterns, probabilities of correct classification (a.k.a. true positive rates) are estimated for all fault classes. A mean number $\overline{P}$ of these probabilities determines total accuracy of engine fault classification by the used network. Applying the probability $\overline{P}$ as a criterion, two analyzed networks, MLP and PNN, are tuned and compared in the sequel.

3. Comparison test case

A gas turbine power plant for natural gas pumping has been chosen as a test case. It is an aeroderivative two shaft engine with a power turbine. In the paper gas turbine diagnosis is analyzed at two operating modes called Mode 1 and Mode 2. They are close to engine maximal and idle regimes and are set in the thermodynamic model by the corresponding gas generator rotation speeds and standard ambient conditions.

Apart from these operating conditions, other 6 gas path variables measured in the power plant are available for monitoring and are used to compute fault patterns. These gas path monitored variables and their normalization parameters a_i are specified in Table 1.

Table 1

Monitored variables

№	Variable's name	a_i
1	Compressor pressure p^*_C	0,015
2	Exhaust gas pressure p^*_{HPT}	0,015
3	Compressor temperature T^*_C	0,025
4	Exhaust gas temperature T^*_{HPT}	0,015
5	Power turbine temperature T^*_{LPT}	0,020
6	Fuel consumption	0,020

The faults are simulated through 9 fault parameters embedded into the model. As shown in Table 2, faults of four main engine modules (compressor, high pressure turbine, power turbine, and combustion chamber) are described by two parameters and an inlet device is presented by one parameter. Maximal change of each parameter equals 5%.

Table 2

Fault parameters

№	Parameter's name
1	Compressor flow parameter
2	Compressor efficiency parameter
3	High pressure turbine flow parameter
4	High pressure turbine efficiency parameter
5	Power turbine flow parameter
6	Power turbine efficiency parameter
7	Combustion chamber total pressure recovery parameter
8	Combustion efficiency parameter
9	Inlet device total pressure recovery factor

Two classification variations are considered in the present paper. The first classification embraces 9 single fault classes formed by the parameters of Table 2. The second classification consists of 4 multiple fault classes corresponding to 4 main power plant modules. The class of each module is created by independent variation of two module fault parameters (see Table 2). Regardless of simulated faults, single or multiple, each class is presented by 1000 patterns.

According to the described structures of monitored variables and fault classes, both compared networks have 6 nodes on the input layer and 9 or 4 nodes on the output layer. As to the hidden layer, the PNN have 9000 or 4000 nodes in accordance with the learning set volumes. For the MLP an optimal hidden node number 27 chosen in study [15] is accepted for the present study. Thus, for two classification variations, the MLP structures are written as 6×27×9 and 6×27×4 while the PNN structures are described by 6×9000×9 and 6×4000×4.

4. Comparison results

4.1. Networks tuning

For the sake of correct results each network should be tailored before the comparison. The MLP was tuned for a diagnostic application in our previous works. In particular, a number 27 of hidden layer nodes and a resilient back-propagation training algorithm have been found the best and were accepted for the present study. As to the newly analyzed technique, PNN, its tuning is described below.

Since practically all PNN's coefficients are determined with the learning set data, the only parameter to tailor the network is the spread B (see Section 1). Although Matlab provides an initial value B = 1, it is not obvious that it will be acceptable for the analyzed diagnostic application. That is why the PNN directly applied to gas turbine diagnosis was tailored. Different spread values were employed and the mean probability $\overline{P}$ (see Section 3) has been computed for each value. It was found that the value ensuring the highest probability depends on classification variation. These values, B=0,35 for the singular fault classification and B=0.40 for the multiple one, were used in the comparative calculations described below.

4.2. MLP and PNN comparison

Two engine operation modes and two classification variations, when changed independently, result in four comparison cases. The network comparison under such different conditions will allow drawing more general conclusions on the networks' accuracy and applicability.

Within each comparison case the same input data were fed to both networks and the mean probabilities $\overline{P}$ were computed for each network. Due to a stochastic nature of the computation, these probabilities are known with some uncertainty. Preliminary studies (see, for example, [13]) have shown that the uncertainty interval can be greater than the probability difference for the compared networks. That is why in the present contribution, the probability computation for each comparison case was repeated 100 times, each time with a new seed (parameter that determine a random number series). The obtained probability values are then averaged resulting in an averaged probability $\overline{P}_{av}$. These probabilities computed for the analyzed networks under all comparison conditions are included in Table 3.

Table 3

Averaged networks diagnostic accuracy (Probabilities $\overline{P}_{av}$)

Network	Single fault classification		Multiple fault classification	
	Mode 1	Mode 2	Mode 1	Mode 2
MLP	0,8184	0,8059	0,8765	0,8686
PNN	0,8134	0,8004	0,8739	0,8653

It can be seen in the table that the application of the PNN to gas turbine diagnosis instead of the MLP causes losses of diagnostic reliability for all comparison cases. These losses of the averaged probability $\overline{P}_{av}$ are 0,0050-0,0055 for single faults and 0,0026-0,0033 for multiple faults. It was estimated in [15] that with the confidence of 97,7% an uncertainty interval for $\overline{P}_{av}$ is ±0,00094 (0,094%). Consequently, the observed losses of diagnostic reliability are statistically significant. On the other hand, the observed in Table 3 losses (0,0041 on average) is not too great against the background of total diagnostic inaccuracy (1- $\overline{P}_{av}$), which is about 0,21 for single faults and 0,13 for multiple faults.

Conclusions

This paper examines the probabilistic neural network in an application to gas turbine diagnosis. To assess diagnostic efficiency and applicability of this network, it is compared with the multilayer perceptron.

A power plant for natural gas pumping has been chosen as a test case. It was presented in the paper by a nonlinear thermodynamic model, with which numerous fault patterns for fault classification were generated.

The networks have been tuned for diagnosing the power plant under analysis. They were then tested under different comparison conditions, using an averaged probability of correct diagnosis as a criterion to choose the best network.

By way of summing up comparison results, the conclusion is that although the perceptron is a little more accurate than the probabilistic network, the latter is recommended for gas turbine diagnosis because it provides confidence estimation for each diagnostic decision, the property very valuable in practice. Thus, the probabilistic neural network can be considered as a perspective technique for real gas turbine monitoring systems. The investigations will be continued to better investigate this new diagnostic technique and to draw a final conclusion on its applicability for gas turbine diagnosis.

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ІМОВІРНІСНІ НЕЙРОННІ МЕРЕЖІ ДЛЯ РОЗПІЗНАВАННЯ ДЕФЕКТІВ ГТД

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Алгоритми ідентифікації дефектів, засновані на вимірюваних параметрах проточної частини, є важливим компонентом систем контролю газотурбінних двигунів. У доповненні до діагностування дефектів проточної частини ці алгоритми також здатні ідентифікувати порушення в роботі датчиків і системи контролю двигуна. В алгоритмах ідентифікації дефектів ГТД широко використовуються методи розпізнавання образів, зокрема, різні нейронні мережі. Ефективність системи контролю залежить від достовірності результатів роботи всіх її компонент, тому для кожної її компоненти повинен бути вибраний найбільш точний метод. Для розпізнавання дефектів ГТД найбільш часто застосовується багатошаровий персептрон, один з типів нейронних мереж. Однак, інший тип, імовірнісна нейронна мережа, також може бути застосований. Дана мережа використовує імовірнісну міру, щоб класифікувати дефекти. У представленій статті імовірнісна мережа спочатку настроюється для застосування до діагностування ГТД і потім порівнюється з персептроном. Порівняння показало, що, в середньому, обидві мережі забезпечують практично однакову достовірність результатів. Імовірнісна мережа рекомендується для реальних систем діагностування тому, що в доповненні до діагностичного рішення дана мережа дає оцінку достовірності цього рішення.

Ключові слова: ГТД, діагностування проточної частини, розпізнавання дефектів, нейронні мережі, імовірнісна нейронна мережа.

ВЕРОЯТНОСТНЫЕ НЕЙРОННЫЕ СЕТИ ДЛЯ РАСПОЗНАВАНИЯ ДЕФЕКТОВ ГТД

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Алгоритмы идентификации дефектов, основанные на измеряемых параметрах проточной части, являются важным компонентом систем контроля газотурбинных двигателей. В дополнении к диагностированию дефектов проточной части эти алгоритмы также способны идентифицировать нарушения в работе датчиков и системе контроля двигателя. В алгоритмах идентификации дефектов ГТД широко используются методы распознавания образов, в частности, различные искусственные нейронные сети. Эффективность системы контроля зависит от достоверности результатов работы всех ее компонент, поэтому для каждой ее компоненты должен быть выбран наиболее точный метод. Для распознавания дефектов ГТД наиболее часто применяется многослойный персептрон, один из типов нейронных сетей. Однако, другой тип, вероятностная нейронная сеть, также может быть применен. Данная сеть использует вероятностную меру, чтобы классифицировать дефекты. В представленной статье вероятностная сеть сначала настраивается для применения к диагностированию ГТД и потом сравнивается с персептроном. Сравнение показало, что, в среднем, обе сети обеспечивают практически одинаковую достоверность результатов. Вероятностная сеть рекомендуется для реальных систем диагностирования потому, что в дополнении к диагностическому решению данная сеть дает оценку достоверности этого решения.

Ключевые слова: ГТД, диагностирование проточной части, распознавание дефектов, нейронные сети, вероятностная нейронная сеть.

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