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A Performance Appraisal of Neural Networks Developed for Response Prediction across Heterogeneous Domains

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***Abstract*—**Deciding the numerous parameters involved in designing a competent artificial neural network is a complicated task. The existence of several options for selecting an appropriate architecture for neural network adds to this complexity, especially when different applications of heterogeneous natures are concerned. Two completely different applications in engineering and medical science were selected in the present study including prediction of workpiece's surface roughness in ultrasonic-vibration assisted turning and papilloma viruses oncogenicity. Several neural network architectures with different parameters were developed for each application and the results were compared. It was illustrated in this paper that some applications such as the first one mentioned above are apt to be modeled by a single network with sufficient accuracy, whereas others such as the second application can be best modeled by different expert networks for different ranges of output. Development of knowledge about the essentials of neural networks for different applications is regarded as the cornerstone of multidisciplinary network design programs to be developed as a means of reducing inconsistencies and the burden of the user intervention.

***Keywords*—**Artificial Neural Network, Malignancy Diagnosis, Papilloma Viruses Oncogenicity, Surface Roughness, Ultrasonic Vibration-Assisted Turning.

I. Introduction

ARTIFICIAL neural network (ANN) has found many applications in various disciplines of science and technology. Typical examples are manufacturing and mechanical engineering [1]-[4], optimization of various parameters resulting in optimal production yield [5]-[10], food and agricultural industries [11],[12], economics [13] and medical sciences [14]-[17] to name but a few. The common practice in developing neural networks is currently focused on dedicated application-oriented networks being trained for single-domain processing. Artificial neural networks in their present status are in fact expert domain-based systems. In this respect they are similar to their intelligent counterparts, expert systems. In a sense, both ANNs and expert systems are practically developed for very narrow ranges of applications. This is in direct contradiction to the basic purpose of ANNs to emulate the human brain's inference faculties. It is basically expected that an ANN be apt to be trained in different skills, while the present ANNs can each deal at most with processes exhibiting a good deal of cohesion. The existing shells, of course, provide platforms for developing expert networks in practically unlimited ranges of applications. However, each skill needs its dedicated network to be sufficiently trained for that skill. The data obtained through experiments exhibit considerably nonlinear correlation. Training of networks for different domains of application is thus too much time consuming whereas, in spite of this deficiency, satisfactory results are hardly achieved. This is more critical for heterogeneous domains as the network parameters should accordingly be changed for different applications. There are numerous options to be decided upon when training a network. Genetic algorithms are currently used for optimizing the network parameters. Whereas may be of assistance in getting around to deciding the network parameters, this is not, in its present form, an adequate substitute for the user intervention. A thorough grasp of the ANN performance for different domain-based applications is most desirable. This streamlines the expectations from ANNs and considerably saves time and effort required for designing dedicated networks and also paves the way for development of more intelligently efficient algorithms. Development of knowledge about the essentials of neural networks for different applications is regarded as the cornerstone of multidisciplinary network design programs to be developed as a means of reducing inconsistencies and the burden of the user intervention.

The authors developed several ANNs for two completely different applications, which are briefly explained in this paper. These applications include prediction of surface roughness of 1.1191 steel in ultrasonic vibration-assisted turning (UAT) and malignancy diagnosis or, to be more specific, prediction of papilloma-viruses oncogenicity.

Vibration-assisted machining has not yet sufficiently benefitted from advanced tools such as artificial neural network modelers. Application of ANN was partially undertaken in [4]. A more thorough study was done by the authors of present paper on the efficiency of different

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networks for UAT surface roughness prediction. The results are briefly described in this paper.

The prognosis of papilloma virus infection is of critical importance because cervical carcinoma remains one of the most common malignancies in the world. Around 500,000 new sufferers are diagnosed and more than 200,000 deaths from cervical cancer are reported annually [18]. Application of advanced tools such as ANNs to papilluma virus infection is, in turn, of great importance.

The performance of the developed ANNs intentionally selected from two heterogeneous domains of engineering and medical science was investigated in the present study. This was done by a critical appraisal of these networks against the available results. It has been illustrated that whereas some problems such as UAT surface roughness prediction can be accurately modeled by a single network; some other problems like oncogenicity prediction can be best modeled with different specialized networks for different risk levels.

II. ANNs for Prediction of Surface Roughness in UAT

An extensive literature is available on ANNs, for example [1]-[17]. For further applied and fundamental literature, references [19]-[28] may be consulted.

The multilayer perceptrons (MLPs) are the most common networks used for innumerable applications, in spite of their relatively low rate of training and large chunks of data required for this purpose. The main merit is that they are easy to use. As will be illustrated later in this section, they yield sufficiently and in many cases more accurate results compared with other networks such as general feed forward, recurrent and modular neural networks.

A MLP was primarily selected for modeling the surface roughness in UAT. Ultrasonic-vibration assisted turning or machining is an advanced technique of metal cutting practice. It has several advantages compared with the conventional machining processes, including reduced machining forces and stresses, higher surface finish, less tool wear and closer dimensional and geometrical tolerances. Additionally, vibration assisted cutting changes the brittle machining of hard-to-cut materials such as ceramics, glass and superalloys to ductile machining, leading to feasible cutting of these materials. Vibration cutting has already been applied to various machining processes such as turning, drilling, milling, grinding, honing, lapping and electrodischarge machining [29].

A typical MLP, as depicted in Fig. 1, consists of a layer of input neurons serving as a data gateway to the network, one or more hidden layers of neurons processing the data received from the input layer and finally a layer of output neurons receiving the processed data and providing the final responses. In this figure Ij (j=1-n) denotes the input, m is the number of neurons in the hidden layer and O_j (j=1-k) is the output. The network is trained how to correlate the input and output through numerous data furnished by the user in a supervised training process.

In the model adopted for the surface roughness, the number of input neurons was n= 4 and the single output was the surface roughness, R_a. Eighty one exemplifiers were employed for training of the network.

In order to model surface roughness in UAT, the results of full factorial experiments for 1.1191 steel adopted from [4] were employed. In a full factorial design of experiments (DOE), eighty one different experiments would be required for three levels of four UAT parameters. In fact, the correct form of permutation of these parameters determines the number of the experiments. The UAT parameters and their triple levels are described later in this section.

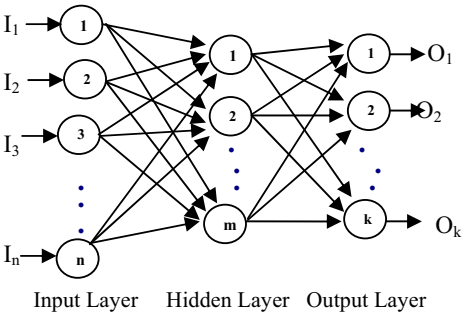

Fig. 1 A typical multilayer perceptron

The output of MLP was naturally different depending on the network parameters. The surface roughness values obtained from the trained MLP with the following parameters for the test data again adopted from [4] are given in Table I: one hidden layer, five processing elements in the hidden layer, TanhAxon as the transfer function both in the hidden and the output layers, step size 1.00 for the hidden layer and 0.10 for the output layer, learning momentum rate of 0.7 for both layers, threshold value as an indication of acceptable error 0.01, and epochs number 342. The experimental results and the errors between these and MLP results are also presented in this table. The UAT parameters in this table are a (μm), ultrasonic vibration; d (mm), depth of cut; f_r (mm/rev), feed rate and v_c, cutting speed. The surface roughness is denoted by R_a (μm).

TABLE I
TEST RESULTS FOR PREDICTING SURFACE ROUGHNESS OF 1.1191 STEEL IN UAT

a μm	d mm	f_r mm/rev	v_c m/min	Ra μm		%
				Exper.	MLP	Error
6	0.5	0.14	3.78	1.37	1.54	12..3
12	0.6	0.14	8.83	1.03	1.13	9.7
12	0.7	0.14	10.8	1.37	1.16	15.3
16	0.8	0.28	17.66	3.74	4.08	9.1

In order to improve the results, several other options were tried as follows: using randomized data, cross validation, using genetic algorithm to optimize the network parameters, decreasing the threshold value, replacing TanhAxon with SigmoidAxon as new transfer function, and using more hidden layers. No improvement could be achieved; instead in some cases much worse results were obtained.

Several other networks were also tried among which some exhibited better results. They were generalized feed forward (GF), modular neural network (MNN), recurrent network (RN), time-lag recurrent network (TRN), and fuzzy logic network (FLN). The results and the errors between these and the experimental results are given in Table II. The UAT parameters were as the same as those presented in Table I.

It is clear from the results presented in Tables I and II that the maximum error occurring in MLP prediction is much lower than other networks. Additionally, MLP's prediction errors have smoother and more uniform distribution.

TABLE II
TEST RESULTS OF DIFFERENT NETWORKS FOR UAT SURFACE ROUGHNESS

GF		MNN		RN		TRN		FLN	
Ra μm	Err. %	Ra μm	Err. %	Ra μm	Err. %	Ra μm	Err. %	Ra μm	Err. %
1.39	1.4	1.44	5	1.74	26.9	1.49	8.7	1.7	24.1
1.51	46.6	1.37	37	1.8	74.8	1.59	54.4	1.3	26.2
1.56	13.9	1.4	1.6	1.12	18.2	1.62	18.2	1.4	2.2
3.85	2.9	3.9	4.3	4.7	25.7	3.73	0.3	4.06	8.6

GF: generalized feed forward, MNN: modular neural network, RN: recurrent network, TRN: time-lag recurrent network, FLN: fuzzy logic network

It should be noted that surface roughness in practice is expresses in discrete values rather than continuous values. In turning and milling operations surface roughness values are usually 0.32, 0.8, 1.6, 3.2, 6.3, 12.5 and 25 μm. It can be said that surface roughness in these operations occurs in six different ranges as follows: (1) 0.32- 0.8, (2) 0.8-1.6, (3) 1.6-3.2, (4) 3.2-6.3, (5) 6.3-12.5, and (6) 12.5- 25 μm. The surface roughness occurred in the experiments and predicted by different networks can thus be concluded as in Table III. It is evident from this table that MLP, GF and MNN could correctly predict the surface roughness ranges. An error in the order of 9-16 μm as having occurred in MLP's prediction (Table 1) is quite acceptable in machining practice especially in the presence of non-violated surface- roughness range as an additional criterion.

TABLE III
EXPERIMENTAL AND PREDICTIVE RESULTS FOR SURFACE ROUGHNESS OF WORKPIECES IN UAT

Exper.	MLP	GF	MNN	RN	TRN	FLN
2	2	2	2	3	2	3
2	2	2	2	3	2	2
2	2	2	2	2	3	2
4	4	4	4	4	4	4

MLP: multilayer perceptron, GF: generalized feed forward, MNN: modular neural network, RN: recurrent network, TRN: time-lag recurrent network, FLN: fuzzy logic network

III. ANN FOR MALIGNANCY DIAGNOSIS

The application of ANN in medical sciences is most exemplified by disease diagnosis. However, a prerequisite to the prediction of papilloma viruses oncogenicity is an in-depth knowledge about the biochemical and structural characteristics of viruses, required for classification of tumorgenic viruses. Application of ANN for this classification needs further effort. This was partially undertaken by the authors in the present study and several networks were developed and evaluated for prediction of papilloma viruses oncogenicity level. In this classification, viruses are identified as high, moderate or low.

The human papilloma viruses (HPVs) are DNA viruses which cause epithelial hyperplasias ranging from benign papillomas to premalignant lesions. These lesions can develop into squamous cell carcinomas [30], [31]. HPV infection is in most cases sexually transmitted and is usually transient. However, it persists in some cases and progress to cervical cancer. Cervical cancer results in the death of approximately 273000 women per year. This toll has the second place after breast cancer. For these reasons, the study of high risk HPV early genes E6 and E7 is of key importance in cancer investigations. High-risk HPVs, including HPV-16 and HPV-18, are associated with squamous intraepithelial lesions that can progress to cervical carcinomas. Approximately 40 among over 100 different HPV types specifically infect anogenital tract mucosa. More than 70% of cervical cancer are however caused by the high-risk genotypes 16 and 18. In fact, cervical papilloma viruses oncogenicity can be caused by persistent high risk HPVs infection which in turn is due to the expression of E6 and E7 oncogenes. These two early HPV genes are of critical importance to tumor formation. Low risk HPVs E6 and E7 have weaker transforming effect compared with moderate and high risk HPVs. Biochemical studies can best provide evidences of the involvement of E6 and E7 in malignancy. [32]-[42]

The information about HPV sequences and papilloma virus data required to develop and train ANN were collected from renowned data bases such as DNA Data Bank of Japan (DDBJ) [43] and Expasy Data base [44]. The acquired parameters were as follows: the oncogenicity level of viruses, E6 and E7 content, amino acid number, molecular weight, theoretical pI, different amino acids, sulfur content, extinction coefficient, estimated half-life, instability index, aliphatic index, and grand average of hydropathicity (GRAVY). The level of virus was used as the only output of the network for each exemplifier. Other parameters amounting to 34 were used as the input to the network. In other words, number of input neurons was n=34 (Fig. 1). The number of exemplifiers used for training of the network was 234. For the sake of space limit the data collected from the data bases could not be presented here. The above mentioned data banks may be consulted in this regard.

The extinction coefficient indicates how much light a protein absorbs at a certain wavelength.

The half-life is the time taken for half of the protein in a cell to disappear after its synthesis in the cell. The instability index is a measure of the stability of protein in a test tube. The aliphatic index of a protein is the relative volume occupied by aliphatic side. The GRAVY of protein is the sum of hydropathy values of all the amino acids, divided by the number of residues in the sequence. For a more comprehensive definition of these parameters, classic literature may be consulted.

For the purpose of modeling the oncogenicity level, also a MLP similar to the modeling of UAT surface roughness was primarily selected. The network was trained several times with the test data adopted from the aforementioned databases. The oncogenicity level obtained from the trained MLP with the following parameters are given in Table IVdenoted by MLP1 prediction: one hidden layer, four processing elements in the hidden layer, TanhAxon as the transfer function in both the hidden and output layers, step size 1.00 for the hidden layer and 0.10 for the output layer, learning momentum rate of 0.7 for both layers, and epochs number 97. In Table IV, the three high, moderate and low oncogenicity levels are indicated by three normalized figures 0.1, 0.5 and 0.9, respectively. The error between the predicted and the database results are also presented.

TABLE IV
TEST RESULTS FOR PREDICTING THE ONCOGENICITY LEVEL

No.	Database Output	MLP1 Prediction		MLP2 Prediction	
		Level	Error%	Level	Error%
1	0.5	0.43	7	0.49	2
2	0.5	0.43	7	0.49	2
3	0.5	0.43	7	0.49	2
4	0.5	0.49	2	0.52	6
5	0.5	0.17	66	0.08	83.6
6	0.5	0.26	48	0.56	12
7	0.1	0.13	30	0.09	10
8	0.1	0.16	60	0.10	0
9	0.1	0.16	60	0.10	0
10	0.1	0.16	60	0.10	0
11	0.1	0.16	60	0.10	0
12	0.1	0.12	20	0.09	10
13	0.9	0.85	5.5	0.90	0
14	0.9	0.80	11	0.88	2
15	0.9	0.82	9	0.87	3
16	0.9	0.86	4.4	0.91	1
17	0.9	0.80	11	0.87	3
18	0.9	0.81	10	0.87	3

In order to improve the results, several other options were also tried. The results were different from the view point of error, in contrary to the UAT surface roughness model where no improvement or even worse results were achieved. Training the network with randomized data resulted in no improvement. Mixed results, in some cases improvement and in others worse results were achieved with cross validation and internal test. Using genetic algorithm to optimize the network parameters, replacing TanhAxon with SigmoidAxon as new transfer function, and using more hidden layers indicated no obvious improvement. Decreasing the threshold value from 0.01 to 0.001 led to considerable decrease in the error, as indicated in Table IV as MLP2 prediction. No noticeable improvement in the results could be achieved by further decrease in the threshold. Instead any further decrease resulted in much longer training time.

Among several other networks tried for modeling the oncogenicity level, generalized feed forward (GF), modular neural network (MNN), and RBF/GRNN/PNN network yielded acceptable results which are presented in Table V. These networks were trained for a threshold of 0.0001 and 20000epochs.

TABLE V
TEST RESULTS OF DIFFERENT NETWORKS FOR ONCOGENICITY PREDICTION

No	GF		MNN		RBF/GRNN/PNN	
	Level	Err. %	Level	Err. %	Level	Err. %
1	0.49	2	0.50	0	0.48	4
2	0.49	2	0.50	0	0.47	6
3	0.48	4	0.50	0	0.47	6
4	0.62	26	0.52	4	0.47	6
5	0.08	84	0.14	72	0.40	20
6	0.13	74	0.19	62	0.48	4
7	0.10	0	0.10	0	0.12	20
8	0.14	40	0.11	1	0.12	20
9	0.15	50	0.11	1	0.12	20
10	0.15	50	0.11	1	0.12	20
11	0.09	10	0.10	0	0.12	20
12	0.90	0	0.08	20	0.13	30
13	0.91	1	0.90	0	0.75	15
14	0.90	0	0.91	1	0.82	9
15	0.90	0	0.89	1	0.76	16
16	0.90	0	0.91	1	0.71	22
17	0.91	1	0.90	0	0.80	11
18	0.90	0	0.89	1	0.74	18

GF: generalized feed forward, MNN: modular neural network

As is clear from Table IV the results of MLP2 are quite acceptable except for the result No. 5. This odd result was persistent for all other options and networks. This may be due to ill-conditioned or wrong data. However, the RBF/GRNN/PNN network could even predict oncogenicity level for this item within an acceptable tolerance of error.

The results presented in Tables IV and V show a tendency towards classification of results depending on the oncogenicity level, as follows: The RBF/GRNN/PNN network can best predict moderate oncogenicity levels. High risks are best predicted by multilayer perceptron and modular neural network. Low risk can be best predicted by multilayer perceptron, generalized feed forward and modular neural network. Ignoring the single ill-conditioned test sample,

multilayer perceptron can predict all risk levels, reliably. For further reliability other competent networks as described above can be consulted.

IV. CONCLUSION

The surface roughness of steel workpieces machined in ultrasonic-vibration assisted turning and cervical papilloma-viruses oncogenicity as showcases of completely different subjects were selected in this study. Several predictive models were developed for them using different artificial neural network architectures and parameters. The results of appraisal of these networks can be concluded as follows:

A multilayer perceptron with one hidden layer and TanhAxon as the transfer function could predict surface roughness of steel components in ultrasonic-vibration assisted turning with an error in the range of 9 to 16%. This is acceptable for the machining practices.

Changing the network parameters, for instance increasing the number of hidden layers, decreasing the threshold, changing the transfer function, randomizing the data and cross validation led to no better results, whereas in some cases worse results were also obtained. This is an indication of highly nonlinear nature of the problem.

Several other networks were also tried among which some exhibited better results. They were generalized feed forward, modular neural network, recurrent network, time-lag recurrent network, and fuzzy logic network. However, the results obtained from the multilayer network were more accurate together with smoother distribution of error.

As far as the ranges of surface roughness are concerned rather than its exact numerical value, which is more common in industry, multilayer perceptron, generalized feed forward, and modular neural network could correctly predict the surface roughness. In this case, decision about the appropriate architectures should be made on the basis of their compatibility with other applications in hand, and training time. Non-violated range of surface roughness can be used as an additional criterion for assessing the model prediction error.

A multilayer perceptron similar to that developed for UAT surface roughness predicting model could not yield satisfactory results. In this case, however, ten times decreasing the threshold resulted in much improved output. Ignoring one single ill-conditioned exemplifier, the error in the response of the rectified network was in the range of 0 to 12%.

Generalized feed forward, modular neural network and RBF/GRNN/PNN also could acceptably model the oncogenicity level when trained with 100 times decreased threshold and 20000 epochs. The last mentioned network could even deal with the single ill-conditioned and predict the relevant response with 20% error.

The performance of the networks might be classified as follows: High risk levels were best predicted by multilayer perceptron and modular neural network within 0-10% and 0-20% ranges of error, respectively. The RBF/GRNN/PNN could best predict moderate risk oncogenicity levels within an error range of 4 to 6% disregarding the ill-conditioned exemplifier. Low risk could be best predicted by multilayer perceptron, generalized feed forward and modular neural network within 0-3%, 0-1% and 0-1% ranges of error. Ignoring the single ill-conditioned test sample, prediction of multilayer perceptron for all risk levels may be taken into consideration and for the final judgment about the risk levels other competent networks as described above is consulted.

In order to further the objectives of the present study, an intelligent and multidisciplinary program can be developed on the basis of the information to be gained on the essentials of different applications by similar investigations. This program helps automatically design expert neural network architecture for each application.

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