A Neural Network Based Diagnostic System for Classification of Industrial Carrying Jobs With Respect of Low and High Musculoskeletal Injury Risk

Rohit Sharma r25sharma@gmail.com
Faculty of Engineering
Dayalbagh Educational Institute
Dayalbagh, Agra, 282110, India

Ranjit Singh rsingh_dei@yahoo.com
Faculty of Engineering
Dayalbagh Educational Institute
Dayalbagh, Agra, 282110, India

Abstract

Even with many years of research efforts, Safety professionals and ergonomists have not yet been established the occupational exposure limits of different risk factors for development of Musculoskeletal disorders (MSDs). One of the main problems in setting such guidelines is to accurately assess the association between exposures and possible occupational disorders or diseases and predict the outcome of any variable. The task of an industrial ergonomist is complicated because the potential risk factors that may contribute to the onset of the MSDs interact in a complex way, and require an analyst to apply elaborate data measurement and collection techniques for a realistic job analysis. This makes it difficult to discriminate well between the jobs that place workers at high or low risk of MSDs. This paper describes a new approach for the development of artificial neural networks applied to classifying the risk of MSDs for industrial carrying jobs. The data set used in this research was collected from Foundry and Sugar industries workers using the physiological variables.The main objective of this study was to to develop an artificial neural network based diagnostic system which can classify industrial jobs according to the potential risk for physiological stressors due to workplace design. The neural network obtained can be used by the ergonomist as a diagnostic system, enabling jobs to be classified into two categories (low-risk and high-risk) according to the associated likelihood of causing MSDs. This system provides a higher proportion of correct classifications than other previous models. So, the system can be used as an expert system which, when properly trained, will classify carrying load by male and female industry workers into two categories of low risk and high risk work, based on the available characteristics factors.

Relevance to industry

A number of workers involve in lifting and carrying loads manually in industries. Such tasks may lead to various types of musculoskeletal injuries to the workers. So, this study was focussed on the development of an artificial neural network-based diagnostic system which can classify industrial jobs according to the low and high risk of MSDs. Such a system could be useful in hazard analysis and injury prevention due to manual handling of loads in industrial environments.

Keywords: Musculoskeletal Injuries, Physiological Risk, Artificial Neural Network

1. INTRODUCTION

Occupational health hazards are common in many sectors and are on the increase. Musculoskeletal disorders (MSDs), which are problems of musculoskeletal system, are significant and costly workplace problems affecting occupational health, productivity and the careers of the working population. MSDs represent a wide range of disorders and are an important cause of morbidity and disability. At the present time, MSDs are one of the most important problems ergonomists encounter in Workplaces around the world [1]. In 2001, the National Institute for Occupation Safety and Health (NIOSH) defined musculoskeletal problems as a group of conditions that involved the nerves, tendons, muscles, and supporting structures such as inter vertebral discs. Studies from around the world have documented the enormous burden of musculoskeletal injuries on individuals and society [2]. These problems are caused by repetitive, awkward, or stressful motions, heavy lifting, frequent twisting and bending, whole body vibration, and psychosocial variables [3, 4, 5, 6, 7]

Work related neck and upper limb problems are very prevalent in nature. In the Netherlands, a survey showed that in 2002 and 2004, 28% of the working population reported neck/shoulder or elbow/wrist/hand symptoms in the previous 12 months. These symptoms were at least partly\caused by work, according to the self-report of the participants [8]. Yearly sick leave due to work related neck and upper limb problems are estimated to be 2 to 4% of all workers. Scutter et al. [9] reported that one third of agricultural workers surveyed reported neck pain at least once a week. Tractor driving was reported most frequently as the activity that contributed to neck pain. Low back pain (LBP) is also the most frequent musculoskeletal problem. Snook [10] estimated the annual direct and indirect costs of back pain to be almost $16 billion. The highest percent of such injuries occurred in service industries (31.9%), followed by manufacturing (29.4%), transportation and public utility (28.8%), and trade (28.4%). The total time lost due to disabling work injuries was 75 million work-days, with the total work accident cost of $47.1 billion, and the average cost per disabling injury of about $16,800. The economic impact of back injuries in the US alone may be as high as $20 billion annually. Nearly 2 million workers suffer from MSDs each year [11].The economic loss due to such disorders affects not only the individual but also the organization and the society as whole [12]. In industrially developing countries (IDCs) the problems of workplace injuries are extremely serious [13]. In many countries the prevention of MSDs among the workforce is considered a national priority [14].

2. METHODOLOGY

2.1 Artificial Neural Network

In neural computing, mathematical processing units (neurons) are linked together by weighted connections. Each neuron processes its weighted inputs according to its activation function, and its output is then connected to the inputs of the next layer of neurons. Networks usually have a non-linear activation function, of which a popular choice is the logistic (sigmoidal) activation function. By allocating appropriate values to the weights, an Artificial Neural Network (ANN) can perform complicated operations on its inputs. A network can be trained to perform a particular operation using a set of training data comprising a series of input patterns for which the correct output is known. Each training pattern is presented to-the inputs in turn. The network weights, originally set to random values, are then optimized using a training algorithm. Training continues until the errors associated with the training set are minimized. Neural networks can solve classification problems when the input data is difficult to describe, and therefore hold promise for medical applications [15].

2.2 ANN Architecture

In this study, a feedforward neural network with error back-propagation training was implemented [16, 17]. During supervised error-back propagation training, input patterns are presented sequentially to the system along with the correct response. The response is provided by the teacher and specifies the classification information for each input pattern. The network learns from experience by comparing the targeted correct response with the actual response. The network parameters (weights and thresholds) are usually adjusted after each incorrect response based on the error value generated. This process of comparison of correct and actual response is continued for each input pattern until all examples from the training set are learned within an acceptable error. During the classification phase, the trained neural network itself operates in a feedforward manner. The input pattern is passed forward through the network one layer at a time from the input to the output, with no feedback. The network should be able to classify accurately in situations not encountered in training. The architecture of an ANN model is shown in figure 1.

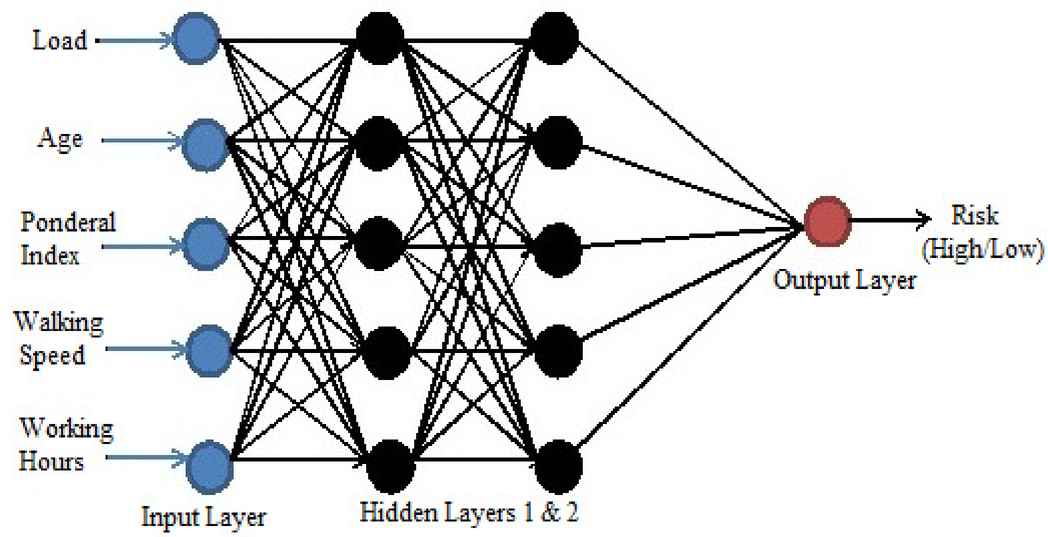

FIGURE 1: The Architecture of the proposed artificial neural network model.

The task of the industrial ergonomist is fairly difficult because the potential risk factors that may contribute to the MSDs in a complex way, and require him or her to apply elaborate data measurement and collection techniques for a realistic job analysis. If an Expert System is made, which can classify the loads carried in different categories of risk, than the potential risks involved can be avoided. Hence, a Neural Network Model which will act as a knowledge base system for the classification of carried load in different risk categories will be of great use. Some researchers also found the successful implementation of the ANN in classifying manual lifting jobs. Karwowski et al. [18] presented a prototype of a neural network-based system for classification of industrial jobs according to the potential risk for LBDs. Although the system was trained using a limited number of data for 60 high and low risk jobs the preliminary results showed that the developed diagnostic system could successfully classify jobs into the low and high risk categories of LBDs based on lifting task characteristics. The jobs were correctly classified into the low and high risk categories in about 80% of cases. Zurada [19] also found that a developed diagnostic system can successfully classify jobs into the low and high risk categories of LBDs based on lifting task characteristics. So, the main objective of this study was to develop an artificial neural network based diagnostic system which can classify industrial jobs according to the potential risk for physiological stressors due to workplace design. Such a system could be useful in hazard analysis and injury prevention due to manual handling of loads in industrial environments.

2.3 Experimental Data for Model Development

This study involved an acceptable load for male and female workers involved in carrying load in high and low risk work. Since the preference of the workers was in head mode so the data taken for training neural network was for head mode only. For training neural network, the data from specially prepared questionnaire and experimental in laboratory of the male and female workers involved in Foundry and Sugar industries were used. Their physiological stress were divided into two groups, high and low risk work based upon the factors load carried, age, ponderal index, walking speed and working hours as the increase or decrease in the values of these factors influence the physiological stress. These factors were applied as the input during network's training and testing. Physiological stress and heart beats per minute records were used to categorize high and low risk work. The low risk and high risk work was defined as those jobs or load carried by male and female workers with physiological stress and heart rate depending upon age with ponderal index, working hour and walking speed.

Mathematically we summarize this as,

$$Y = f\left(\mathrm{L, A, PI, WS, WH}\right) \quad \text{............ (1)}$$

Where,

Y= .1 < Physiological risk factor < .9
L= 8 < Load <51 Kg
A = 21 < Age < 52 years
PI = 23 < Ponderal index < 26.2
WS = 2 < Walking Speed < 3.9 km/hr
WH = 5 < Working Hours < 8 hrs.

2.4 Normalization of Training Data

The values of the input variables for male and female workers are given in table1 and 2. To prevent network's saturation [19], these variables were normalized in between [0.1 0.9] by a programme written in Matlab. The Y variable (risk of load carrying) takes values of 0.9 or 0.1 for high and low risk work, respectively. This variable was used only as teacher's response during the network's training using error back propagation algorithm.

2.5 Network Training and Development of Model

The network was trained in MATLAB environment software programmed by exploiting Neural Network Toolbox model version R.2010.a. This software is chosen due to its capabilities and ability to provide solutions in technical computing. Among various training algorithm available, Levenberg-Marquardt (LM) training function was selected because it has the fastest convergence ability [20]. Out of the 72 sets of observations with low and high risk values recorded for male workers 65 sets were used for training and development of model and in case of female workers out of 66 sets of observations with low and high physiological risk 56 sets were used for training of the ANN.

2.6 MAT LAB Programme for Development of ANN Model

```
clc;
clear all;
close all;
x=data
x=[normal1(x(:,1)) normal1(x(:,2)) normal1(x(:,3)) normal1(x(:,4)) normal1(x(:,5)) normal1(x(:,6))];
t=x(1:65,6);p=x(1:65,1:5);
 p=p';t=t';
net=newff(minmax(p),[5,5,1],{'tansig','tansig','purelin'});
net.trainParam.show = 20;
net.trainParam.epochs = 3000;
net.trainParam.goal = 1e-8;
[net,tr]=train(net,p,t);
p=x(1:72,1:5);p=p';d=x(1:72,6);
 y=sim(net,p);y=y';
 k=[y d];p=p';
plot(k)
figure(2)
k1=[p(:,1) y];
plot(k1)
figure(3)
k2=[p(:,2) y];
plot(k2)
figure(4)
k3=[p(:,3) y];
plot(k3)
figure(5)
```

```
k4=[p(:,4) y];
plot(k4)
figure(6)
k5=[p(:,5) y];
plot(k5)
```

Above Mat lab code include file of data which refers to male and female workers observations sets given in table 1 and 2.

Test run of Model

After the training of the network the model so trained and developed is tested for all sets of observation in case of male (72) and female workers (66).

3. RESULTS AND DISCUSSION

3.1 Simulation Results- Male Workers

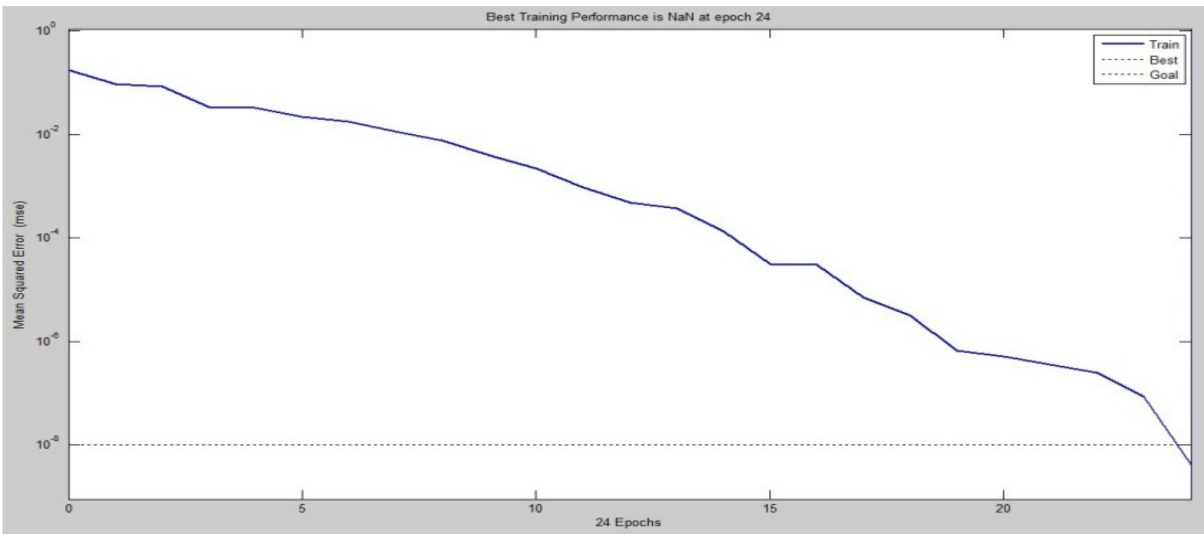

FIGURE 2: Training error versus number of training cycles (Epochs)

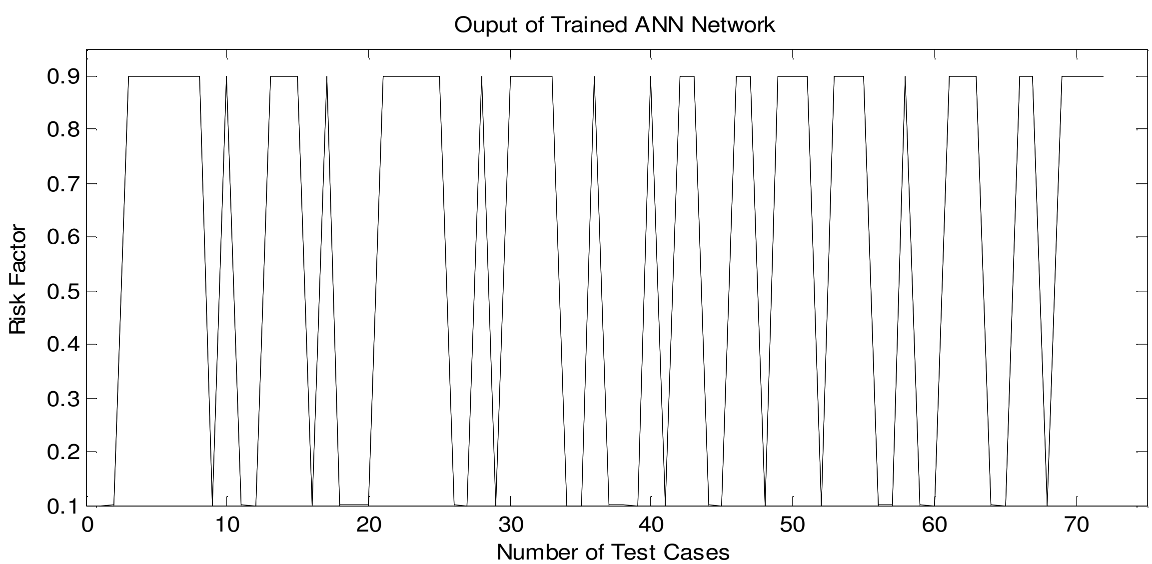

FIGURE 3: Output of trained ANN network

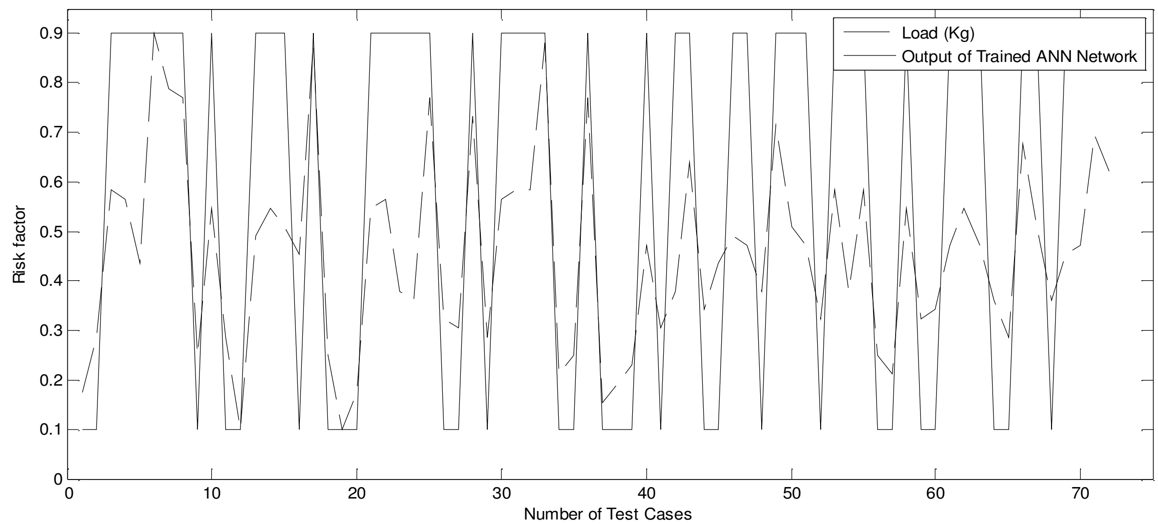

FIGURE 4: Comparison of output of trained ANN network and 1st input

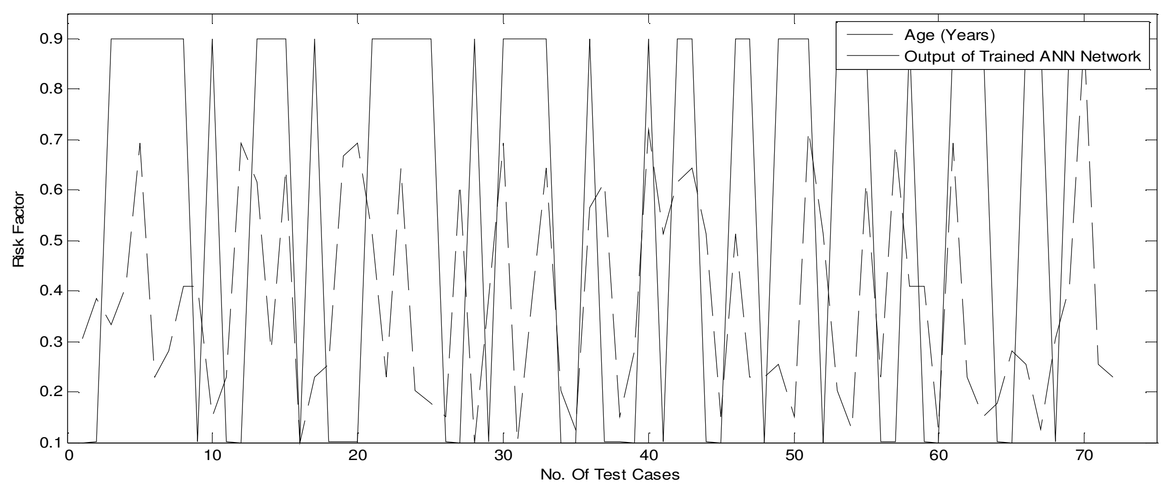

FIGURE 5: Comparison of output of trained ANN network and 2nd input

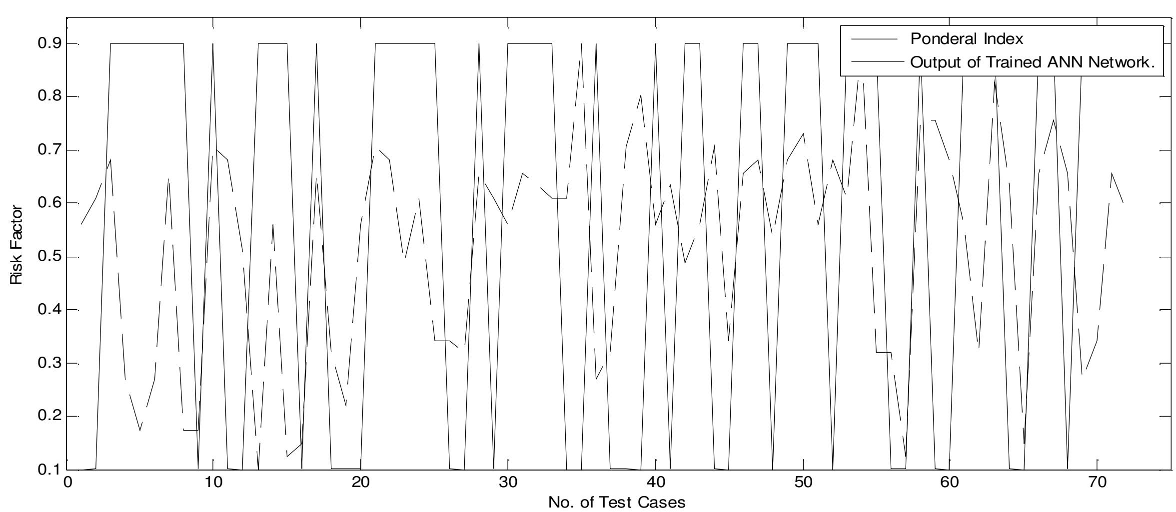

FIGURE 6: Comparison of output of trained ANN network and 3rd input

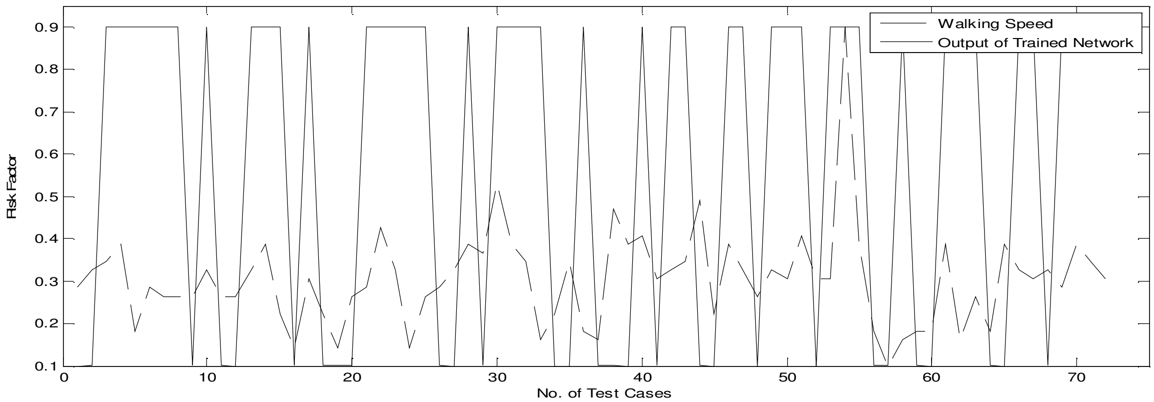

FIGURE 7: Comparison of output of trained ANN network and 4th input

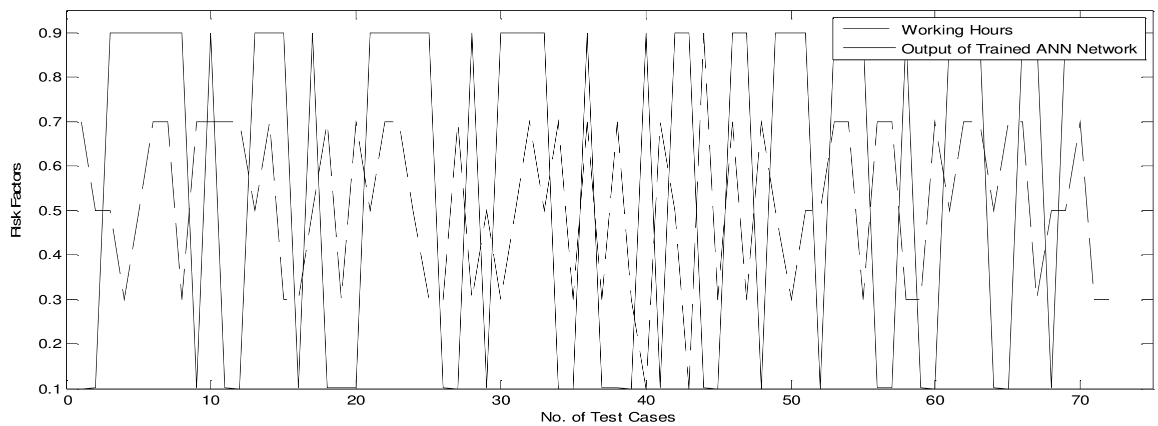

FIGURE 8: Comparison of output of trained ANN network and 5th input

Figure 2 shows the training of the neural network for the first 65 sets of observation of the male workers and figure 3 shows the output of the trained neural network in the interval of [0.1 0.9]. Figures 4 to 8 show the plotting of trained neural model for all the sets of observations with the inputs of the ANN and the figures showed that as the magnitude of load, age, walking speed and working hours of these factors increases, the risk increases.

3.2 Simulation Results – Female Workers

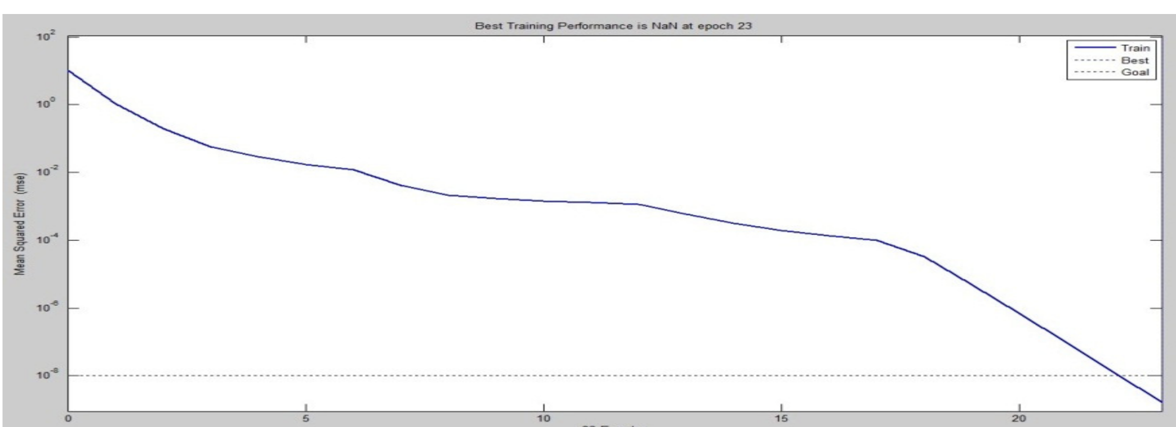

FIGURE 9: Training error versus number of training cycles (Epochs)

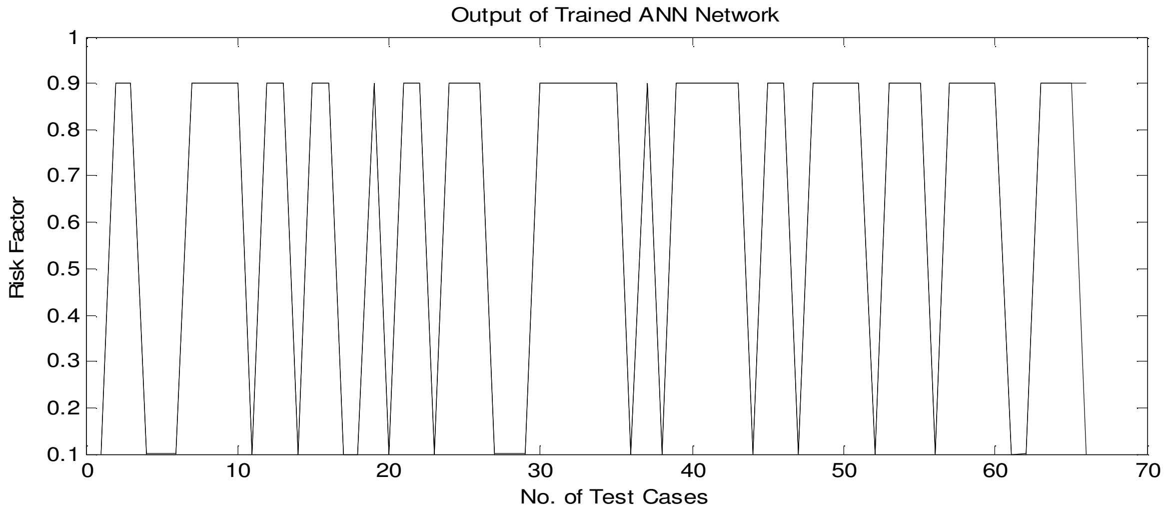

FIGURE 10: Output of trained ANN network

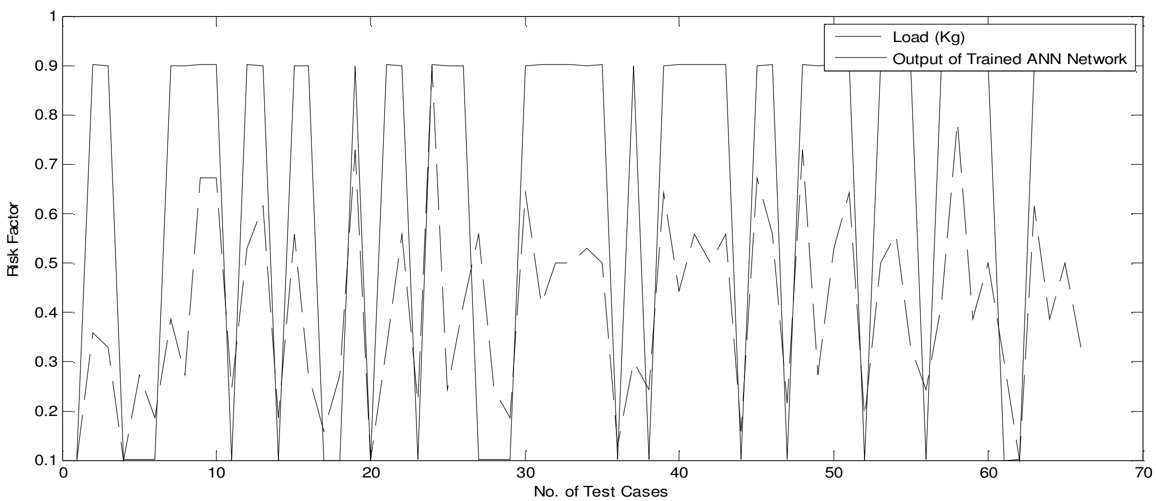

FIGURE 11: Comparison of output of trained ANN network and 1st input

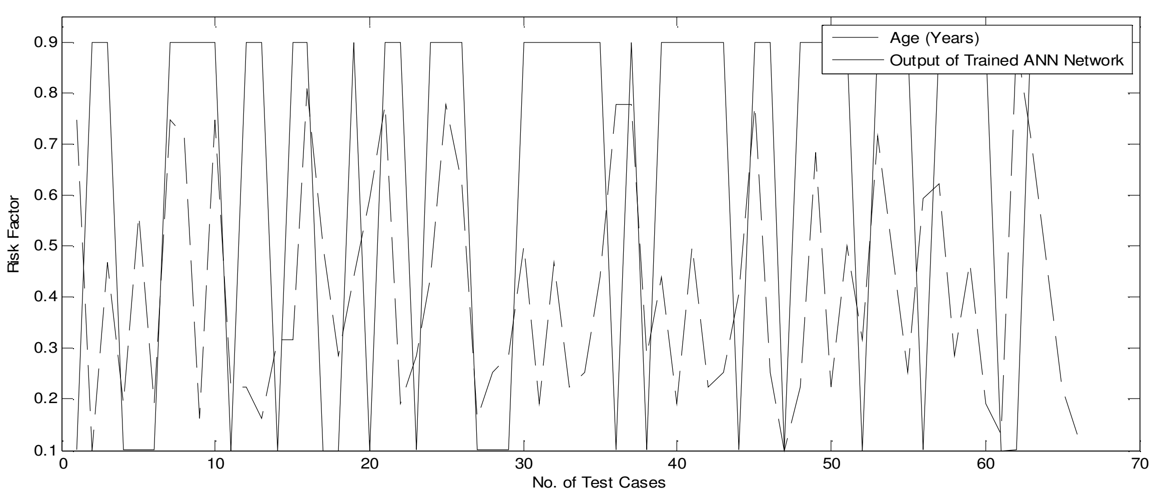

FIGURE 12: Comparison of output of trained ANN network and 2nd input

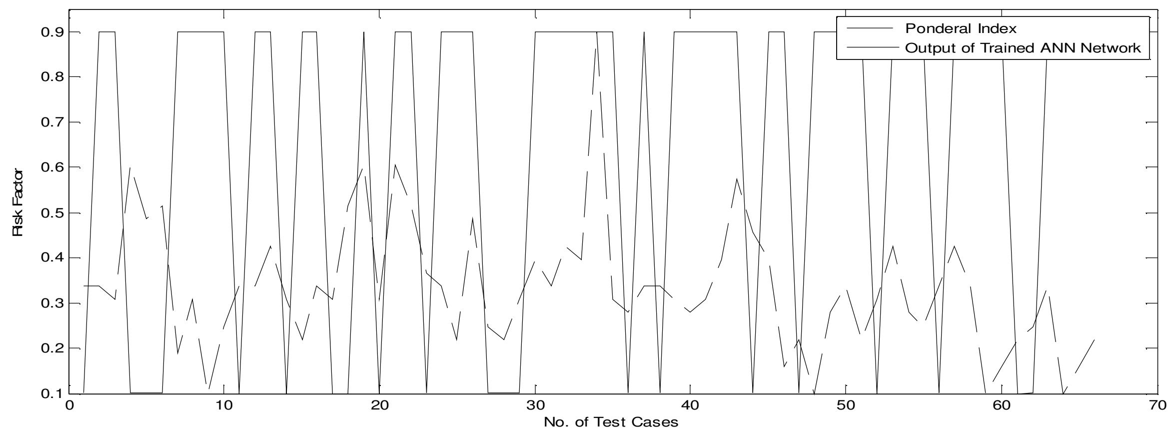

FIGURE 13: Comparison of output of trained ANN network and 3rd input

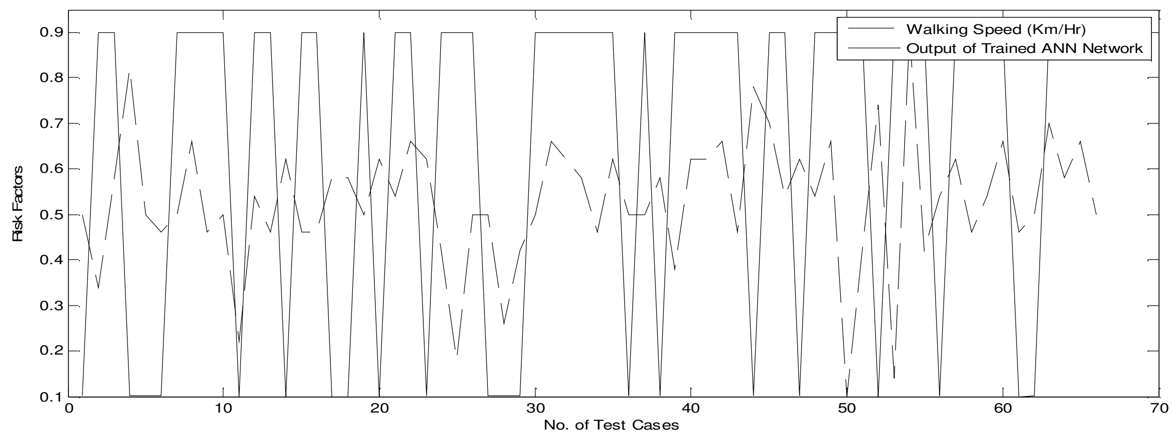

FIGURE 14: Comparison of output of trained ANN network and 4th input

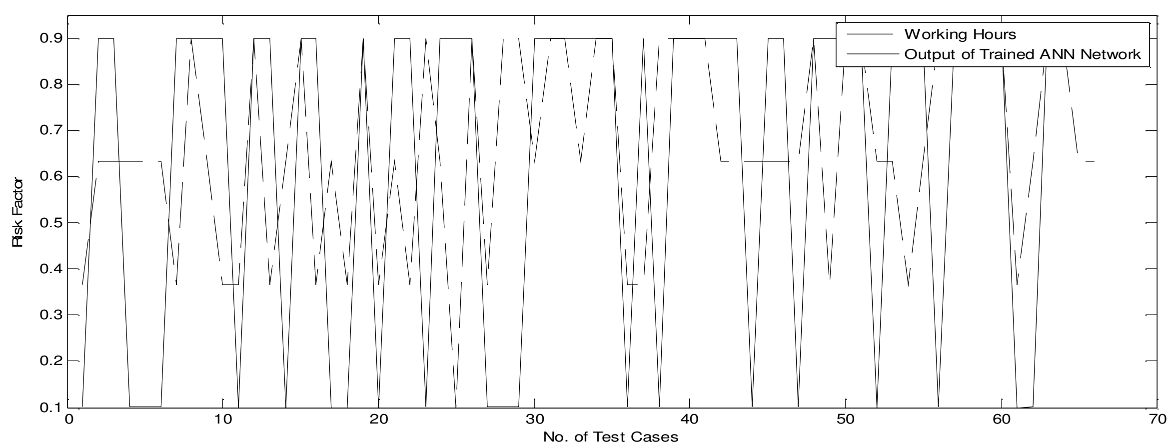

FIGURE 15: Comparison of output of trained ANN network and 5th input

Figure 9 shows the training of the neural network for the first 56 sets of observation of the female workers and figure 10 shows the output of the trained neural network in the interval of [0.1 0.9]. Figures 11 to 15 show the plots of trained neural model for all the sets of observations with the inputs of the ANN and show that as the magnitude of load, age, walking speed and working hours of these factors increases or decreases, the risk also increases or decreases.

TABLE 1: The percentage variation in experimental and simulated results (Male workers)

S.No.	Load (kg)	Age (year)	Ponderal Index	Walking Speed	Working Hours	Risk		Percentage variation (%)
						Physiological	ANN Simulation	
1.	12	29	24.8	2.7	8	Low	Low	0.014517
2.	18	32	25	2.9	7	Low	Low	0.006739
3.	34	30	25.3	3	7	High	High	0.000349
4.	33	33	23.6	3.2	6	High	High	-0.00087
5.	26	44	23.2	2.2	7	High	High	-0.00753
6.	51	26	23.6	2.7	8	High	High	0.002771
7.	45	28	25.2	2.6	8	High	High	0.006082
8.	44	33	23.2	2.6	6	High	High	0.002217
9.	16	33	23.2	2.6	8	Low	Low	0.289529
10.	32	23	25.4	2.9	8	High	High	0.002228
11.	18	26	25.3	2.6	8	Low	Low	0.0421
12.	8	44	24.6	2.6	8	Low	Low	0.019635
13.	29	41	22.9	2.9	7	High	High	-0.00398
14.	32	28	24.8	3.2	8	High	High	-0.00056
15.	30	42	23	2.4	6	High	High	-0.00216
16.	27	21	23.1	2	6	Low	Low	0.000605
17.	50	26	25.2	2.8	7	High	High	0.003725
18.	16	27	23.8	2.4	8	Low	Low	0.043644
19.	8	43	23.4	2	6	Low	Low	0.029657
20.	12	44	24.8	2.6	8	Low	Low	0.006035
21.	32	37	25.4	2.7	7	High	High	-0.00055
22.	33	26	25.3	3.4	8	High	High	0.000216
23.	23	42	24.5	2.9	8	High	High	-0.02341
24.	22	25	25	2	7	High	High	-0.02488
25.	44	24	23.9	2.6	6	High	High	0.001041
26.	20	23	23.9	2.7	6	Low	Low	-0.15115
27.	19	41	23.8	2.9	8	Low	Low	-0.21189
28.	42	21	25.2	3.2	6	High	High	-0.0024
29.	18	32	25	3.1	7	Low	Low	0.005013
30.	33	44	24.8	3.9	6	High	High	-0.00117
31.	34	21	25.2	3.2	7	High	High	0.010481
32.	34	32	25.1	3	8	High	High	0.000466
33.	50	42	25	2.1	7	High	High	0.003174
34.	14	25	25	2.4	8	Low	Low	0.042572
35.	16	22	26.2	3	6	Low	Low	0.00782
36.	44	39	23.6	2.2	8	High	High	0.00255
37.	11	41	23.8	2.1	6	Low	Low	0.006824
38.	13	23	25.4	3.6	8	Low	Low	-0.21649
39.	15	28	25.8	3.2	6	Low	Low	0.004896
40.	28	45	24.8	3.3	5	High	High	-0.01014
41.	19	37	25.1	2.8	8	Low	Low	0.033211
42.	23	41	24.5	2.9	7	High	High	0.005072
43.	37	42	24.8	3	5	High	High	0.000906
44.	21	37	25.4	3.7	9	Low	Low	-0.01588
45.	26	23	23.9	2.4	6	Low	Low	0.001795
46.	29	37	25.2	3.2	8	High	High	-0.00503
47.	28	26	25.3	2.9	6	High	High	0.002094
48.	23	26	24.7	2.6	8	Low	Low	-0.25723

49.	41	27	25.3	2.9	7	High	High	0.002542
50.	30	23	25.5	2.8	6	High	High	0.022776
51.	28	45	24.8	3.3	7	High	High	-0.00756
52.	20	37	25.3	2.8	7	Low	Low	0.086335
53.	34	25	25	2.8	8	High	High	0.001987
54.	23	22	26.2	5.7	8	High	High	0.003125
55.	34	41	23.8	3.2	6	High	High	-0.00051
56.	16	26	23.8	2.2	8	Low	Low	0.124038
57.	14	44	23	1.8	8	Low	Low	-0.11788
58.	32	33	25.6	2.1	6	High	High	0.000293
59.	20	33	25.6	2.2	6	Low	Low	-0.36982
60.	21	22	25.3	2.2	8	Low	Low	-0.06034
61.	28	44	24.8	3.2	7	High	High	-0.00712
62.	32	26	23.8	2.1	8	High	High	0.000925
63.	28	23	25.9	2.6	8	High	High	0.000795
64.	22	24	25.1	2.2	7	Low	Low	-0.03006
65.	18	28	23.1	3.2	8	Low	Low	-0.00894
66.	39	27	25.2	2.9	8	High	High	0.003506
67.	30	22	25.6	2.8	6	High	High	0.101124
68.	22	29	25.2	2.9	7	Low	Low	1.025248
69.	27	33	23.6	2.7	7	High	High	-0.00596
70.	28	52	23.9	3.2	8	High	High	-0.00727
71.	40	27	25.2	3	6	High	High	0.001816
72.	36	26	24.9	2.8	6	High	High	0.000844

TABLE 2: The percentage variation in experimental and simulated results (Female workers)

S.No.	Load (kg)	Age (year)	Ponderal Index	Walking Speed	Working Hours	Risk		Percentage variation (%)
						Physiological	ANN Simulation	
1.	12	42	23.2	2.8	6	Low	Low	0.01732
2.	21	21	23.2	2.4	7	High	High	0.015001
3.	20	33	23.1	3	7	High	High	0.009011
4.	12	24	24.1	3.6	7	Low	Low	-0.04509
5.	18	36	23.7	2.8	7	Low	Low	-0.19893
6.	15	24	23.8	2.7	7	Low	Low	0.064624
7.	22	42	22.7	2.8	6	High	High	0.001357
8.	18	41	23.1	3.2	8	High	High	0.023939
9.	32	23	22.4	2.7	7	High	High	0.001186
10.	32	42	22.9	2.8	6	High	High	0.004302
11.	17	25	23.2	2.1	6	Low	Low	0.06396
12.	27	25	23.2	2.9	8	High	High	-0.00896
13.	30	23	23.5	2.7	6	High	High	0.000986
14.	15	28	23.1	3.1	7	Low	Low	0.012451
15.	28	28	22.8	2.7	8	High	High	-0.00821
16.	18	44	23.2	2.7	6	High	High	-0.00098
17.	14	34	23.1	3	7	Low	Low	0.057785
18.	18	27	23.8	3	6	Low	Low	0.077637
19.	34	32	24.1	2.8	8	High	High	-0.01928
20.	12	37	23.1	3.1	6	Low	Low	0.004904
21.	20	43	24.1	2.9	7	High	High	0.014895
22.	28	24	23.8	3.2	6	High	High	0.000232

23.	16	27	23.3	3.1	8	Low	Low	0.009932
24.	40	32	23.2	2.6	7	High	High	-0.01064
25.	17	43	22.8	2	5	High	High	-0.00042
26.	23	38	23.7	2.8	8	High	High	-0.01407
27.	28	23	22.9	2.8	6	Low	Low	0.006109
28.	17	26	22.8	2.2	8	Low	Low	0.010578
29.	15	27	23.1	2.6	8	Low	Low	0.007079
30.	31	34	23.4	2.8	7	High	High	-0.00805
31.	23	24	23.2	3.2	8	High	High	0.02017
32.	26	33	23.5	3.1	8	High	High	-0.0127
33.	26	25	23.4	3	7	High	High	0.028119
34.	27	26	25.1	2.7	8	High	High	9.01E-06
35.	26	32	23.1	3.1	8	High	High	-0.01147
36.	13	43	23	2.8	6	Low	Low	-0.03634
37.	19	43	23.2	2.8	6	High	High	-0.00078
38.	17	27	23.2	3	8	Low	Low	0.002666
39.	31	32	23.1	2.5	8	High	High	-0.01008
40.	24	24	23	3.1	8	High	High	0.004068
41.	28	34	23.1	3.1	8	High	High	-0.01198
42.	26	25	23.4	3.2	7	High	High	-0.00291
43.	28	26	24	2.7	7	High	High	7.06E-05
44.	14	31	23.6	3.5	7	Low	Low	0.158553
45.	32	43	23.4	3.3	7	High	High	-0.01279
46.	28	26	22.6	2.9	7	High	High	-0.00345
47.	16	21	22.8	3.1	7	Low	Low	0.009754
48.	34	25	22.4	2.9	8	High	High	-0.00569
49.	18	40	23	3.2	6	High	High	-0.00407
50.	27	25	23.2	1.8	8	High	High	0.016232
51.	31	34	22.8	2.6	8	High	High	-0.01043
52.	15	28	23.1	3.4	7	Low	Low	-0.01214
53.	26	41	23.5	1.9	7	High	High	0.00024
54.	28	33	23	3.8	6	High	High	-0.01196
55.	20	26	22.9	2.6	7	High	High	0.030324
56.	17	37	23.2	2.9	8	Low	Low	-0.16531
57.	23	38	23.5	3.1	8	High	High	-0.0135
58.	36	27	23.2	2.7	8	High	High	-0.00911
59.	22	33	22.4	2.9	8	High	High	-0.00933
60.	26	24	22.6	3.2	8	High	High	-0.00599
61.	19	22	22.8	2.7	6	Low	High	-799.415
62.	12	47	22.9	2.8	7	Low	Low	0.095916
63.	30	41	23.2	3.3	8	High	High	-0.01307
64.	22	33	22.4	3	8	High	High	-0.00999
65.	26	25	22.6	3.2	7	High	High	-0.00702
66.	20	22	22.8	2.8	7	Low	High	-784.575

Neural Network model developed in this study can predict physiological stress in the male and female workers involved in Foundry and Sugar industry based on five input parameters. The results obtained using LM training for back propagation NN give good prediction and are validated with experimental values as indicated in Table 1 and 2. These results suggest that ANN is a powerful tool for predictive application. ANN captures the intricate relationship among various process parameters and can be integrated readily into an existing environment. Table 3 shows a comparison between results of past studies models and the current study model in terms of accuracy in classifying physiological stress in Low and High risk and the current study has an edge over the past studies, as it provides a higher proportion of correct classifications (97%) than other previous models.

TABLE 3: Comparison of the results of previous studies and current approach.

Zurada et. al., 1997	Asensio-Cuesta et. al. 2010	Current Study
industrial jobs for LBDs about 75%	Highly repetitive lifting industrial jobs for LBDs about 87%	Industrial carrying jobs for MSDs about 97%

4. CONCLUSION

The results of this study show that an artificial neural network-based diagnostic system can be used as an expert system which, when properly trained, will allow us to classify carrying loads by male and female workers into two categories of low and high risk work, based on the available characteristics factors. The developed neural network based classification system shows great promise because it identifies and classifies industrial jobs into the high and low risk potential for physiological risk and significantly reduces the time consuming job analysis and classification performed by traditional methods like mathematical modeling. Finally this technique open new overseas of parameters estimation, function approximation, optimization and online control of the complex system. Future work will focus on validation of the ANN architecture, and consider utilization of other input variables for the modeling, including individual characteristics of the workers, and the job stressors such as job satisfaction, work autonomy, workload, and other psychosocial parameters.

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