

# Identification of Industrial Health using ANN

Deepak Goswami, Padma Lochan Hazarika, and Kandarpa Kumar Sarma

**Abstract**—The customary practice of identifying industrial sickness is a set traditional techniques which rely upon a range of manual monitoring and compilation of financial records. It makes the process tedious, time consuming and often are susceptible to manipulation. Therefore, certain readily available tools are required which can deal with such uncertain situations arising out of industrial sickness. It is more significant for a country like India where the fruits of development are rarely equally distributed. In this paper, we propose an approach based on Artificial Neural Network (ANN) to deal with industrial sickness with specific focus on a few such units taken from a less developed north-east (NE) Indian state like Assam. The proposed system provides decision regarding industrial sickness using eight different parameters which are directly related to the stages of sickness of such units. The mechanism primarily uses certain signals and symptoms of industrial health to decide upon the state of a unit. Specifically, we formulate an ANN based block with data obtained from a few selected units of Assam so that required decisions related to industrial health could be taken. The system thus formulated could become an important part of planning and development. It can also contribute towards computerization of decision support systems related to industrial health and help in better management.

**Keywords**—Industrial, Health, Classification, ANN, MLP, MSE.

## I. INTRODUCTION

ALL the developing countries have assigned a very significant role to industrialization in their programmes of economic development. The reason is that the industrial sector is recognized as an indispensable tool of a stable economy. India has been trying to accelerate the rate of economic development through industrialization ever since the beginning of the planning era [1]-[9]. Very often, industrial sickness is identified using certain traditional techniques based on surveys, field visits and analysis of available data. The customary practice of identifying industrial sickness is a set traditional techniques which rely upon a range of manual monitoring and compilation of financial records. It makes the process tedious, time consuming and often are susceptible to manipulation. Therefore, certain readily available tools are required which can deal with such uncertain situations arising out of industrial sickness. It is more significant for a country like India where the fruits of development are rarely equally distributed. In this paper, we propose an approach based on

Artificial Neural Network (ANN) to deal with industrial sickness with specific focus on a few such units taken from a less developed north-east (NE) Indian state like Assam. The proposed system provides decision regarding industrial sickness using eight different parameters which are directly related to the stages of sickness of such units. The mechanism primarily uses certain signals and symptoms of industrial health to decide upon the state of a unit. Specifically, we propose an ANN based block with data obtained from a few selected units of Assam so that required decisions related to industrial health could be taken. The system thus formulated could become an important part of planning and development. It can also contribute towards computerization of decision support systems related to industrial health and help in better management.

The ANN is a non-parametric tool which can learn from the surrounding environment and use the knowledge thus acquired for subsequent decision making similar to biological systems [11]. This ability of the ANN has made it a popular mechanism for dealing with a range of applications in engineering, technology, finance, management and related disciplines. The system thus formulated could become an important part of planning and development. It can also contribute towards computerization of decision support systems related to industrial health and help in better management.

The rest of the paper is organized as follows. Section II includes a brief theoretical background relevant for the work. Primarily, this section focuses on different stages of industrial health (Section II-A) and the basics of ANN (Section II-B). Section III describes the details of the proposed soft-computational framework for analyzing industrial health. The experiments performed and the results derived are included in Section IV. Section V concludes the description.

## II. BACKGROUND

Here, we briefly discuss certain background notions relevant for the work.

### A. Industrial Sickness and its Types

In India, despite governmental efforts, the rate of industrial growth has failed to pick up [1]. Certain industries have been plagued by sickness corroding the narrow industrial base. This is more pertinent for the NE Indian state of Assam. Therefore, it is important to identify the stages of industrial sickness and the related signals and symptoms as per the guidelines of Reserve Bank of India (RBI) are given below [2]:

1) *Normal Unit*-A normal unit is characterized by the efficient functioning of its functional areas like production, marketing, finance and personnel. In other words, a unit can be called

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healthy or in a normal state (NS) when it is earning profits, the current ratio is more than one, net worth is positive and debt-equity ratio is good [2] [3] [4].

2) *Tending Towards Sickness*- At this stage a unit shows certain initial aberration in any of its functional areas. In other words, the unit faces some environmental constraints. At this time, the unit is said to be tending towards sickness (TS). The distinctive features of this stage are decline in profit in the last year as compared to the previous year and loss estimated in the current year [4] [5].

3) *Incipient Sickness*-The continuation of the deterioration in the functional areas of the unit, results in the actual setting in of industrial sickness. This stage is termed as incipient sickness (IS). At this stage, the unit incurs cash losses but imbalance in the financial structure may not be apparent [6] [7] [8] [9].

These industrial health stages are summarized in the Table I. The  $\uparrow$  sign indicates growth,  $\downarrow$  means fall, NC indicates no change and Nil denotes zero value for particular sample industrial data.

### B. ANN

ANN is a non-parametric information processing mechanism which can learn from the surrounding and use the knowledge subsequently [10]. ANNs are preferred as classifiers for their ability to provide optimal solution to a wide class of arbitrary classification problems [11]. Multi Layered Perceptron (MLP) is a class of feed-forward ANN trained with (error) Back Propagation (BP). It has found wide spread acceptance in several classification, recognition and estimation applications [10].

1) *Multi Layered Perceptron Based Learning*: The fundamental unit of the ANN is the McCulloch-Pitts neuron (1943). The MLP is the product of several researchers: Frank Rosenblatt (1958), H. D. Block (1962) and M. L. Minsky with S. A. Papart (1988). Backpropagation (BP), the training algorithm, was discovered independently by several researchers (Rumelhart et. al.(1986) and also McClelland and Rumelhart (1988)). A simple perceptron is a single McCulloch-Pitts neuron trained by the perceptron algorithm is given as:

$$O_x = g([x][w] + b) \quad (1)$$

where  $[x]$  is the input vector,  $[w]$  is the associated weight vector,  $b$  is a bias value and  $g(x)$  is the activation function. Such a setup, namely the perceptron is able to classify only linearly separable data. A MLP, in contrast, consists of several layers of neurons held together by inter-linked connectionist weights which are assigned values randomly at the beginning and updated continuously during training. These together generate a non-linear computing. The connectionist weights retain the learning during training and facilitate an adaptation to reach the desired goal. The expression for output in a MLP with one hidden layer is given as:

$$O_x = \sum_{i=1}^N \beta_i g([w]_i x + b_i) \quad (2)$$

where  $\beta$  is the weight value between the  $i^{\text{th}}$  hidden neuron. Such a set-up maybe depicted as in Fig. 1. The process of

adjusting the weights and biases of a perceptron or MLP is known as *training*. The perceptron algorithm (for training simple perceptrons) consists of comparing the output of the perceptron with an associated target value. The most common

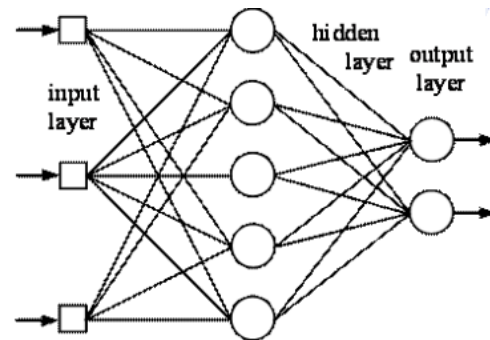


Fig. 1 Multi Layer Perceptron

training algorithm for MLPs is BP which is an extended form of the method used to train the perceptron. This algorithm entails a backward flow of the error corrections through each neuron in the network. The process of adjusting the weights and biases of a perceptron or MLP is known as *training*. The perceptron algorithm (for training simple perceptrons) consists of comparing the output of the perceptron with an associated target value. The most common training algorithm for MLPs is BP which is an extended form of the method used to train the perceptron. This algorithm entails a backward flow of the error corrections through each neuron in the network.

In the most basic form, an ANN requires an input and should be associated with a reference which it tracks during each training iteration. The output, at the end of each training epoch, is compared with the reference and a corresponding adaptation of the connectionist weights are carried out. This is repeated till the output of the ANN is nearly equal to that of the reference. One cycle through the complete training set forms one epoch. The above is repeated till MSE meets the performance criteria. While repeating the above the number of epoch elapsed is counted. A few methods used for MLP training includes Gradient Descent BP (GDBP), Gradient Descent with Momentum BP (GDMBP), Gradient Descent with Adaptive Learning Rate BP (GDALRBP), Gradient Descent with Adaptive Learning Rate and Momentum BP (GDALMBP) and Gradient Descent with Levenberg-Marquardt BP (GDLMBP).

### III. PROPOSED ANN BASED FRAMEWORK FOR IDENTIFICATION OF STAGES OF INDUSTRIAL SICKNESS

We propose a ANN based framework designed to deal with industrial sickness. It is like a decision supports mechanism using eight different parameters of industrial health. These parameters are related to the stages of sickness of such units identified on the basis of field survey conducted in certain areas from a less developed NE Indian state like Assam. The proposed system primarily receives symptoms of industrial health of multiple units which are mapped to corresponding industrial health states using the non-linear processing generated by the ANN.

The eight identified parameters are production volume ( $x_1$ ), marketing ( $x_5$ ), personnel ( $x_6$ ), net worth rise ( $x_7$ ) and net worth fall ( $x_8$ ) as summarized in Table I.

TABLE I  
STAGES OF INDUSTRIAL SICKNESS AND ASSOCIATED SYMPTOMS

Sickness States	Production ( $x_1$ )	Profit ( $x_2$ )	Working Capital ( $x_3$ )	Loss ( $x_4$ )	Marketing ( $x_5$ )	Personnel ( $x_6$ )	Net worth rise ( $x_7$ )	Net worth fall ( $x_8$ )
Normal (N)	↑	↑	↑	Nil	↑	↑	↑	Nil
Tending to Sickness (TS)	↑	↓	NC	↑	NC	NC	NC	↑
Incipient Sickness (IS)	↓	↓	↓	↑	↓	↓	↓	↑
Close (C)	↓	↓	↓	↑	Nil	Nil	Nil	↑

The identified stages of an industrial unit are normal (N), Tending to Sickness (TS), Incipient Sickness (IS) and Close (C). The association between the symptoms and the industrial health stages are distinctly shown by the Table I. Fig. 2 shows the system model used to formulate a decision support mechanism to identify the stages of sickness of industrial units. For training the ANN as part of the industrial health identification system, the conditions and contents of the Table I are codified using binary logic. For example, the growth state is represented by 11, fall by 10, NC denoted by 01 and Nil 00. The parameters have a set of codes as described while the industrial health have another group of unique class states. The specification of the MLP used to formulate the proposed industrial health identification system is summarized in Table II. The ANN block is trained to certain number of sessions with data of five numbers of each of the industrial units. The

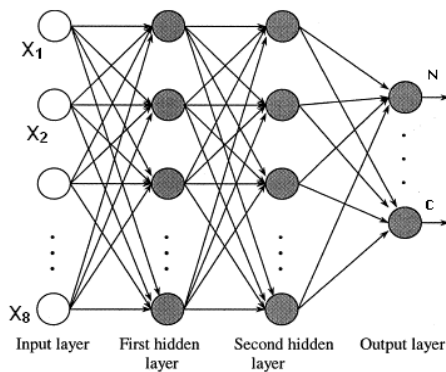


Fig. 2 Soft-computational framework to identify industrial health

TABLE II  
SPECIFICATIONS OF THE ANN BASED MODEL

Item	Description
ANN Type	Multi Layer Perceptron
Data Size	300 sets of data, 16x4 size each
Input vector size	16
Class	4
Number of Hidden Layers	2
Learning Rate	0.1 to 0.5
Activation Function	Tansig-Logsig-Purelin
MSE Convergence goal	10 <sup>-4</sup>

TABLE III  
SELECTION OF APPROPRIATE TRAINING METHOD AND TRAINING RESULTS

Type	Epochs	MSE	Time in sec.s	Remark
GDBP	100	0.34	3.53	Goal not reached
	200	0.085	5.35	
	500	0.002	9.14	
	1000	0.001	17.3	
GDMBP	100	0.32	3.31	Goal not reached
	200	0.081	4.87	
	500	0.002	9.01	
	1000	0.001	16.4	
GDLMBP	10	0.0003	2.3	Goal reached after 10 (av.) epochs and within 3 sec.s

training is sustained as required by specific goals fixed. During training, the ANN block captures the variations shown by the sample data presented to them. Table III shows certain training results related to the proposed approach. Each network is trained using *GDLMBP* as it proves to be computationally efficient (Table III).

#### IV. EXPERIMENTAL RESULTS AND DISCUSSION

The success of the proposed system is dependent on the configuration, training, data set and subsequent validation of the system. The configuration of the MLP formulating the system is summarized in Table II. There are two hidden layers used in the system. The size of the first hidden layer is fixed with respect to number of neurons in the input layer and by

TABLE IV  
PERFORMANCE VARIATION AFTER 1000 EPOCHS DURING TRAINING OF AN ANN WITH VARIATION OF SIZE OF THE HIDDEN LAYER

Case	Size of hidden layer (x input layer)	MSE	Precision in %
1	0.75	$1.2 \times 10^{-3}$	87.1
2	1.0	$0.56 \times 10^{-3}$	87.8
3	1.25	$0.8 \times 10^{-4}$	87.1
4	1.5	$0.3 \times 10^{-4}$	90.1
5	1.75	$0.6 \times 10^{-4}$	89.2
6	2	$0.7 \times 10^{-4}$	89.8

TABLE V  
TESTING DATA SET REFLECTING AVERAGE VALUES OF FIVE MEDIUM AND LARGE SCALE UNITS TENDING TOWARDS SICKNESS

Sickness States	Production, in tons	Profit in %	Working Capital, Rs. $\times 10^6$	Loss, %	Marketing, %	Personnel,	Net worth rise, %	Net worth fall, %
2007	241	6.3	305	0	20	165	1.1	0
2008	231	5.5	289	0	18	158	1.0	0
2009	203	1.3	275	0	13	155	0.7	0
2010	191	0.0	238	2.1	5	141	0	1.4

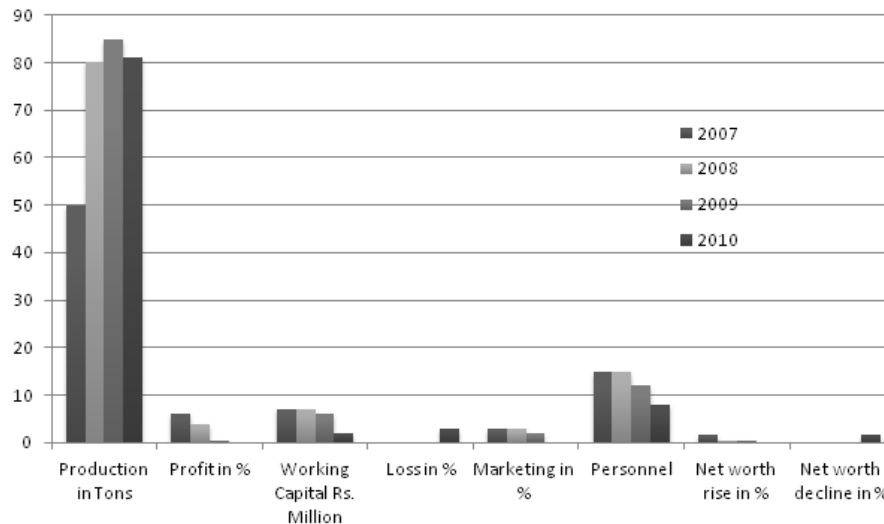


Fig. 3 ANN predicted results for four consecutive years of a TS unit

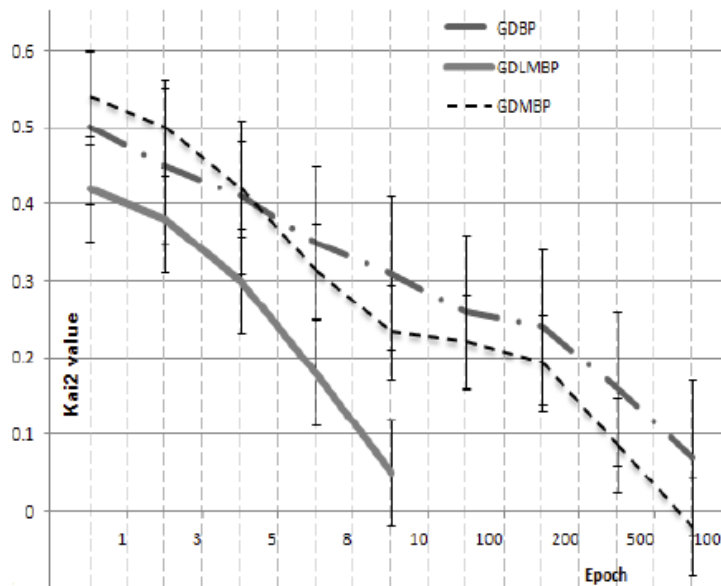


Fig. 4 kai<sup>-2</sup> plot between actual and desired results for three different training methods

following the considerations summarized in Table IV. It shows the performance obtained during training by varying the size of the hidden layer. The case where the size of the hidden layer taken to be 1.5 times to that of the input layer is found to be computationally efficient. Hence, the size of the hidden layer is fixed at 1.5 times to that of the input layer. The next layer also is provided a length of 1.5 times to that of the

first hidden layer which is fixed following the considerations as summarized in Table IV. Table III shows certain training results related to the proposed approach. The process logic is described by the block diagram shown in Fig. 2.

The proposed approach is likely to face multiple situations which it must learn first and be ready for application. Hence,

speed and low computational complexity is critical. It is directly linked to a proper selection of the training algorithm which is of utmost importance. The values in Table III indicate that the *GDMBP* is marginally faster than *GDBP*. The fastest training is carried out by *GDLMBP*. It achieves the MSE convergence goal within the first ten epochs. As the *GDLMBP* turns out to be the fastest and the most reliable training method, the ANN training using it is used for subsequent testing. After training, ANN based framework shows a success rate of around 95 to 98%. The trained ANN is tested with a set of data as shown in Table V. It represents average sets of data of stages showing small, medium and large scale units tending towards sickness over a three year period. The data clearly show that while working capital remains constant, profit starts to fall. It is a sign of TS. The ANN provides accurate prediction of industrial health for all the thirty sets of training data considered for validation of performance. At the end of atleast fifteen trials, the success rate of around 95 to 98% is consistently achieved. Some of the related works have been reported in [11].

When the trained ANN is tested using the data samples collected from field survey, the predicted results generated closely matches the expected results. A set of trials for four consecutive years are repeated and the results noted. A summarized set of results for certain TS units are shown in Fig. 3.

A  $kai^{-2}$  plot between actual and desired results for three different training methods is shown in Fig. 4. The plot also includes error bars for each of the training method. For *GDMBP*, the error falls to satisfactory level within the first ten epochs which reflects the efficiency of the system in terms of computational cost and accuracy. The proposed system thus identifies the industrial health of sample units with satisfactory performance. The above results have been derived using field survey data of around 315 medium and small scale units taking 10% random samples for training, 15% for validating and 20% for testing. Thus, the framework proposed is effective for medium and small scale units in identifying the industrial health and the approaching state in the immediate future.

## V. CONCLUSION

Here, we have proposed an ANN based framework for identifying the industrial health of a few units taken from a less developed NE Indian state like Assam. More specifically, the proposed framework formulates certain decision support mechanism to decide upon industrial sickness using eight different parameters which are directly related to the stages of sickness of such units. The mechanism primarily identifies a few stages of industrial health using various selected inputs which are critical in effective functioning of any related decision support system. The system thus formulated could become an important part of planning and development and contribute towards computerization of decision support systems related to industrial health and help in better management.

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