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Determination of Effective Manufacturing Safety Strategy using Artificial Neural Network

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ABSTRACT

Accidents always have a negative impact on the society, apart from causing a mishap, its occurrence in manufacturing brings great anguish to the victims while the organization suffers loss in productivity and profit. Though there are useful relevant manufacturing safety resources, the allocation may be expensive if proper tool is not used in the implementation. Therefore, suitable safety strategy is required for good safety management planning. This research work employs the artificial neural network (ANN) to allocate effectively, some given set of safety intervention programme (SIP) resources

Six SIP activities were identified and are coded as: SIP-A, SIP-B, SIP-C, SIP-D, SIP-E and SIP-F for personal protective equipment (PPE), motivation of workers, accident investigation, guarding, awareness creation and training, respectively. Accident data and expenditure on safety interventions were collected from a tobacco company in Nigeria for a range of 16years. The data were then analysed using combinatorial analysis and ANN, where record of annual expenditure on the safety interventions and number of accidents occurrence were the input and output, respectively.

Combination analysis yielded 62 (sixty-two) new combinations. It was observed that the combinations ADEF, ACDEF and ABDEF gave a fairly low mean square error, an evidence of applicability in time of scarce resources. However, training (SIP-F) was identified as being significantly present in the first 32 combinations. Thus, ANN serves as better tool for planning and managing manufacturing safety programme.

Keywords: *safety intervention, combinations, strategy, resources, accidents*

1. INTRODUCTION

A strategy moves an industry through quality development phases: it develops worker's understanding of quality, experience with quality methods and the industry capability to implement quality programmes and actions. According to [1], strategies remain in the paper format when needed resources are not allocated and capacities not developed. Also, occupational injuries continue to be one of the major work environment challenges facing legislators, organizations and workers worldwide [2]. It is therefore imperative to recognize the reasons for the high rate of accidents and poor industrial safety track record in developing countries (especially in Nigeria). Some people cite the lack of experience of people from developing countries with the technology and machinery designed in developed nations as a cause [3]. As a result, industrial employers must find ways to best communicate hazard information to their employees and promote safety in the workplace. Thus to improve safety related services in an industry, a way of reducing cost should be introduced and proper strategy be employed.

However, widely acceptable causes reported in literature include but not limited to, human factors, deficient maintenance, environmental factor, lack of management commitment and non recognition of safety programme as an investment rather than just spending on safety. Perhaps, the major problem may be due to sparse information on the use of leading of assessing safety programme. Another may be inappropriate formulation of safety programme. Strategy and optimum allocation of needed resources. Although, various approaches have been reported in the literature [1, 4], however the use of Artificial Neural network (ANN) for safety programme evaluation is dearth in the literature especially predicting the expected performance of an effective safety programme.

The ultimate aim is to employ as much as possible the applicable activities in order to maximize the effectiveness in improving safety and health performance. However, it is impractical to implement all or most elements concurrently, therefore, the priority of implementation should be determined for manufacturing enterprises refocusing its resources on individual elements (activities)at a time [5]. Nevertheless, it was reported that at least minimum of three activities is required to have a meaningful prevention programme [1] But, there is need to have best strategy that yields optimum resources consumption for a cost – effective safety programme planning and managing an effective manufacturing safety programme using ANN. This research work however focus on allocating resources of a given set of safety interventions in order to reduce accident rate in manufacturing industries using ANN.

2. METHODOLOGY

Data Collection and analysis

Data were collected on yearly basis for a range of 16years (1993 – 2008) from Tobacco Company in Nigeria on annual record of accidents and annual expenditure on safety intervention programmes (SIP) as presented in Table 1.

Table 1: Cost of the Safety Interventions Programme (in Naira) with Respected Number of Accidents per Year

Year	Cost of SIP-A ₦	Cost of SIP-B ₦	Cost of SIP-C ₦	Cost of SIP- D ₦	Cost of SIP-E ₦	Cost of SIP-F ₦	No of Accidents
1993	1650960	2628400	10150000	4860000	360000	4088000	98
1994	2026800	1192000	861600	1800000	0	3440000	80
1995	2089440	952600	2696900	1290000	60000	3332000	77
1996	2193840	553600	5755700	440000	160000	3152000	72
1997	1734480	2309200	7703000	4180000	280000	3944000	94
1998	2465280	483800	13709000	1770000	420000	2684000	59
1999	2193840	553600	5755700	440000	160000	3152000	72
2000	1985000	1351600	361920	2140000	40000	3152000	82
2001	1734480	2309200	7703000	4180000	280000	3944000	94
2002	2340000	5000	10038000	750000	300000	2900000	65
2003	2862000	2000000	25332000	5000000	800000	2000000	40
2004	120000	2100000	25055000	0	100000	150000	14
2005	1958000	1561000	185000	5000000	600000	170000	16
2006	2550000	2522000	100015000	0	1500000	40000	8
2007	2000000	2406000	5085000	0	1200000	1320000	9
2008	848000	2040000	12088000	1000000	200000	70000	11

Safety interventions were however classified according to [2] as personal protective equipment (PPE), motivation of workers, accident investigation, guarding, awareness creation and training. These are represented as SIP-A, SIP-B, SIP-C, SIP-D, SIP-E and SIP-F respectively.

The data were analysed by employing Artificial Neural Network (ANN). During the training phase of the ANN application, supervised learning took place. The following are the steps carried out during the training process: assemble the training data, preprocessing the set of training data (Normalizing), Creating and initializing the network object, Training the network, Simulating the network response to new inputs, Unnormalizing the output and Performing linear regression between the network outputs (unnormalized) and the targets in order to check the quality of the network training.

i. Assembling the Training Data

The training set was made up of the inputs (SIP costs) of all the six SIP (i.e. SIP-A – SIP-F) over 16 years (i.e. from 1993 – 2008) that were collected from the company and analysed as well as the targets (the number of accidents) over the same number of years. Therefore, the various SIP costs represent the input *p* and the number of accidents represents the target *t* which is the output.

ii. Preprocessing the Set of Training Data

(Normalizing): The approach used for scaling the network inputs and targets was to normalize the mean and standard deviation of the training set with the function *mapminmax*. The use of *mapminmax* is illustrated with the following code.

$$[pn, ps] = mapminmax(p);$$

$$[tn, ts] = mapminmax(t);$$

The network is trained to produce outputs that falls in the range [-1, 1].

iii. Creating and Initializing the Network Object

The feed forward network was created with the function *newff*. The code below creates and also initializes the network.

$$net = newff(pn, tn, [4\ 5], \{'tansig', 'softmax', 'purelin'\}, 'trainrp')$$

By default, 60% of the training data is used for the training set, 20% for validation set and the remaining 20% for testing set.

$$net = init(net);$$

iv. Training the Network

The training process requires a set of carefully selected data which have proper network behaviour as the network inputs *p* and outputs *t*. The weights and biases are iteratively adjusted to minimize the network performance function during training. The default performance function for the feed forward networks is the mean square error *MSE* (which is the average squared error between network outputs *a* and the target outputs *t*. ANN displays the results of the validation graphically and numerically by comparing the forecasted results to the actual results using the mean square error (*MSE*) formula. The *MSE* approach was chosen as it lies close to the center of normal distribution, thus, if errors are assumed to be normally distributed, minimizing the mean square error corresponds to other preferred optimizations.

$$MSE = \frac{1}{p}\sum_{p=1}^{p}\sum_{i=1}^{n}(d_{i,p} - a_i)^2$$

Where $d_{i,p}$ equals desired output of output unit i for input pattern p and a_i equals observed output of output unit i. Also P equals total number of patterns in the data set, while n equals the number of output units.

v. Simulation

The code below was used to simulate the network.

$$an = sim(net, pn);$$

vi. Postprocessing (unnormalizing Outputs):

The setting structure *ts* was used to convert the outputs back to the same units that were used for the original targets. The following code performs this.

$$a = mapminmax(\text{'reverse'}, an, ts);$$

vii. Performing Linear Regression between the Network Outputs (unnormalized) and the Target:

The postprocessing of the network's trained set was performed by the command *postreg*. This command performs a linear regression between each element of the network response and the corresponding target and returns *m* (slope of the linear regression), *b* (intercept of the linear regression) and *r* (regression R-value) where R=1 means a perfect correlation between the outputs and the targets [6]. This is done in order to check the quality of the network training.

$$[m, b, r] = postreg\ (a, t).$$

Combinations

The combinatorial analyses of the SIP were carried out using the combination formula as given below:

$${}^{n}C_{r} = \frac{n!}{r!(n-r)!}$$

$$Where\ n = total\ number\ of\ SIP\ (= 6)$$

$$r = selected\ number\ of\ SIP$$

Formulation of Safety Strategy

After a good regression fit has been obtained during the training, combinations of the safety intervention were introduced into the network after been pre-processed The new combinations were obtained by allocating zero values to one SIP per time throughout the years of study to obtain a factor mix of five, four three and two combinations

MATLAB 7.7.0.471 (R2008b) was employed for the simulation. The choice was due to its versatility and interactive nature of its numerical computations.

The network training was then carried out using the Resilient Back propagation (Rprop) training algorithm. The stop criteria were based on the mean-square error (MSE) analysis. The best result was obtained for the ANN which comprised four neurons in the first hidden layer, five neurons in the second hidden layer, and a single neuron in the output layer. The transfer functions used for these three layers were tansig, softmax and purelin, respectively. The inputs were pre-processed using the normalizing technique which sought relevant direction for the former so that variance can be maximized. For validation, input/target pairs of untrained data (not known by the ANN) were presented to the network to determine how well it predicts the corresponding outputs.

3. RESULTS

The Regression Plot

This gives the association or relatedness between the SIP costs and the number of accidents during training, validation, testing and mean of the three (testing, validation and training) plots with the R=0.99961 in Figure 1 below, it shows that the degree to which the outputs and targets are related and change together is 99.96%. The line of best fit equation is A = T + 0.00042.

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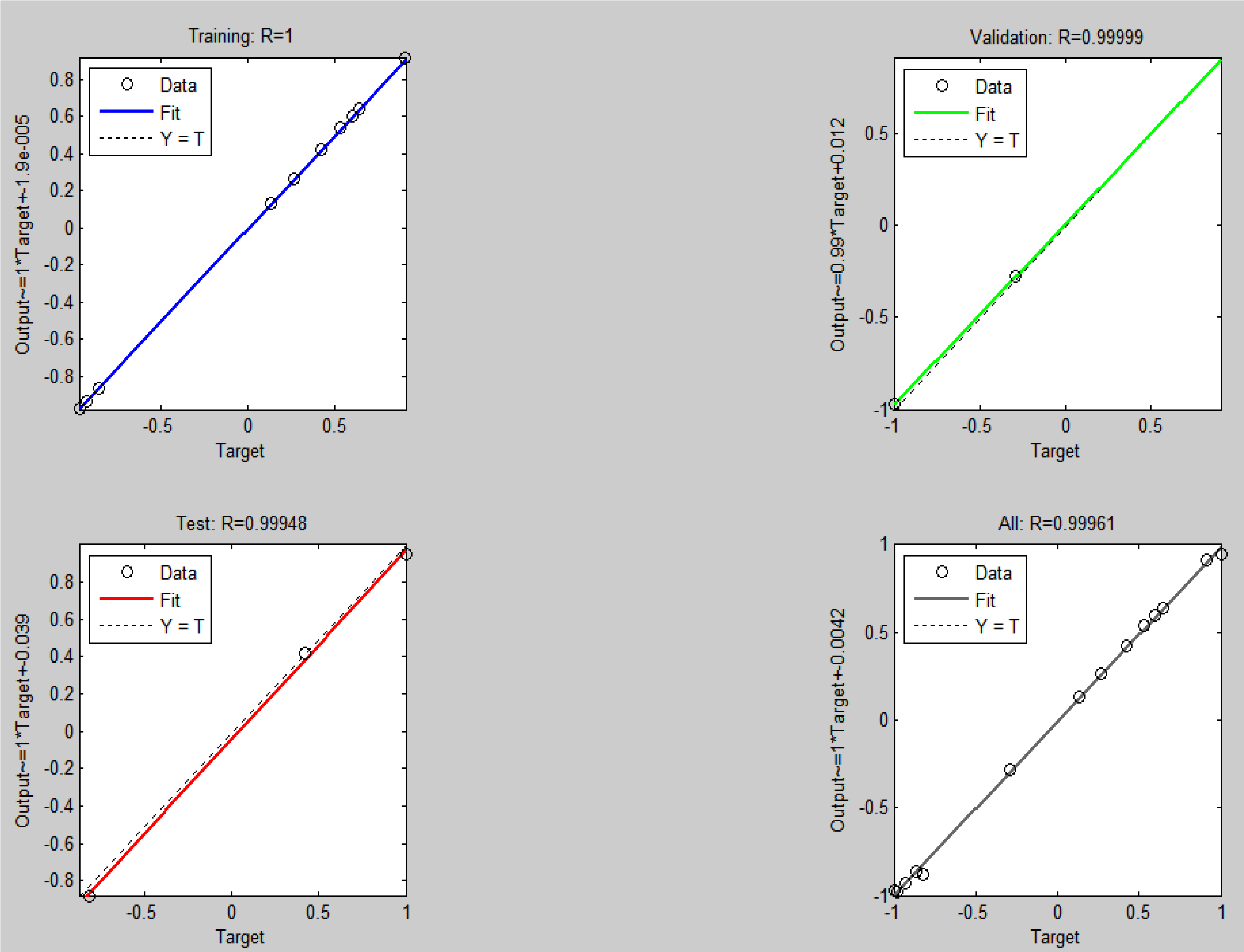

Figure 1: Regression Plots

Combination Analysis Results

Table 2 shows all the 63 (sixty three) combinations of the SIP with their respective mean square error (MSE) value.

4. DISCUSSIONS

After a good regression fit has been obtained during the network training, the network was then saved in the MATLAB directory. The other combinations of five, four, three, two, and one were then analysed as shown in Table 2 and all the combinations were then compared graphically with the actual values of the accidents rate. The deviation of the new values from the actual value is measured from the mean squared error (MSE).

For the combinations of five factors (I.E. ${}^{6}C_{5}$), zero values were allocated to one factor per time during the year of study to obtain a factor mix of ABCDE, ABCDF, ABCEF, ABDEF, ACDEF, and BCDEF. The same process was repeated for the combinations of four, three, two and one while their remaining factors were assigned values of zeros.

It can be deduced that the best safety intervention mix for the tobacco company was when the six interventions were allocated at a time i.e. ABCDEF. This produced the lowest MSE value of 0.74. Also it was observed that the first thirty-two combinations have factor F being predominant in their combinations, this shows that factor F (training) is really significant among all other intervention factors.

However, other combinations like: ADEF, ACDEF and ABDEF gave a fairly low mean square error, an indication that useful application in time of scarce resources. The graphs in Figures 2 – 5 show that the ANN predicted values shows the similar trend with the actual values, this validates the use of ANN model employed.

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Table 2: Analysis of the Combinations

S/N	Combination	Factors Combined	Mean Squared Error	S/N	Combination	Factors Combined	Mean Squared Error
1	${}^6C_6$	ABCDEF	0.74	33	${}^6C_2$	BD	2142.59
2	${}^6C_4$	ADEF	15.28	34	${}^6C_3$	BCD	2215.34
3	${}^6C_5$	ACDEF	19.44	35	${}^6C_3$	BDE	2267.54
4	${}^6C_5$	ABDEF	31.24	36	${}^6C_4$	BCDE	2274.84
5	${}^6C_2$	CF	51.67	37	${}^6C_2$	CD	2480.47
6	${}^6C_2$	EF	56.61	38	${}^6C_3$	CDE	2488.49
7	${}^6C_3$	BEF	57.43	39	${}^6C_2$	DE	2488.61
8	${}^6C_4$	BCEF	58.64	40	${}^6C_3$	ABD	2492.84
9	${}^6C_4$	ACDF	60.39	41	${}^6C_1$	D	2603.03
10	${}^6C_1$	F	67.49	42	${}^6C_4$	ABCD	2635.15
11	${}^6C_3$	ADF	70.51	43	${}^6C_4$	ABDE	2796.56
12	${}^6C_3$	CEF	82.24	44	${}^6C_5$	ABCDE	2847.72
13	${}^6C_4$	ABEF	108.11	45	${}^6C_3$	BCE	2899.73
14	${}^6C_4$	CDEF	108.91	46	${}^6C_2$	BE	2927.33
15	${}^6C_3$	DEF	114.28	47	${}^6C_4$	ABCE	2978.57
16	${}^6C_3$	AEF	116.12	48	${}^6C_3$	ABE	2982.45
17	${}^6C_3$	ACF	132.76	49	${}^6C_2$	AB	2990.97
18	${}^6C_3$	CDF	141.92	50	${}^6C_3$	ABC	2998.97
19	${}^6C_4$	ACEF	146.96	51	${}^6C_1$	B	3018.08
20	${}^6C_5$	ABCEF	147.08	52	${}^6C_3$	ACE	3025.70
21	${}^6C_2$	AF	167.32	53	${}^6C_2$	BC	3028.01
22	${}^6C_5$	BCDEF	172.45	54	${}^6C_2$	AE	3051.01
23	${}^6C_3$	BCF	179.51	55	${}^6C_2$	AD	3065.28
24	${}^6C_5$	ABCDF	180.37	56	${}^6C_2$	CE	3109.24
25	${}^6C_2$	DF	182.73	57	${}^6C_2$	AC	3124.18
26	${}^6C_4$	BDEF	184.05	58	${}^6C_3$	ACD	3126.17
27	${}^6C_4$	ABDF	198.43	59	${}^6C_1$	A	3138.21
28	${}^6C_4$	ABCF	216.12	60	${}^6C_1$	E	3140.07
29	${}^6C_2$	BF	247.85	61	${}^6C_3$	ADE	3157.07
30	${}^6C_3$	ABF	255.36	62	${}^6C_4$	ACDE	3157.79
31	${}^6C_4$	BCDF	304.70	63	${}^6C_1$	C	3223.64
32	${}^6C_3$	BDF	346.52				

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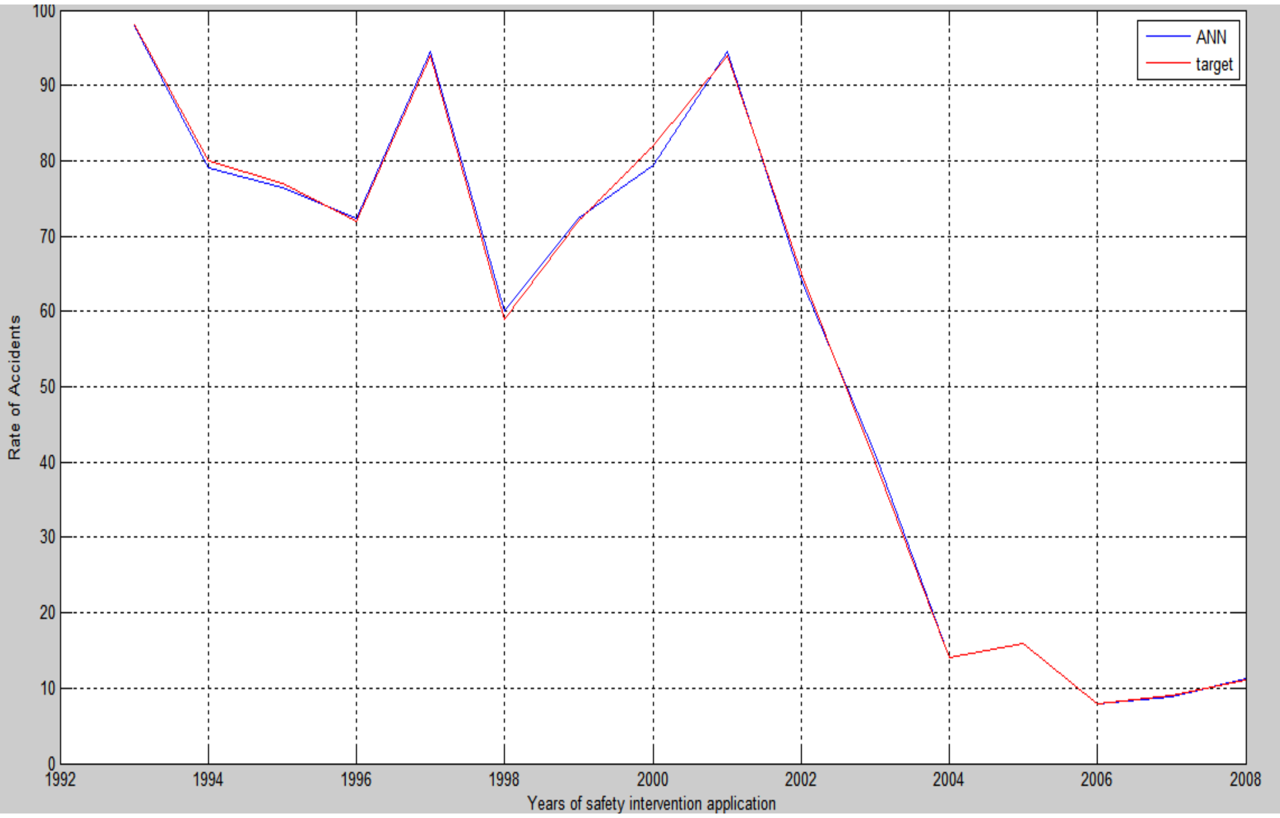

Figure 2: Comparison of Rate of Accidents between the Actual (Target) and Predicted Values for all the SIP (i.e. ABCDEF)

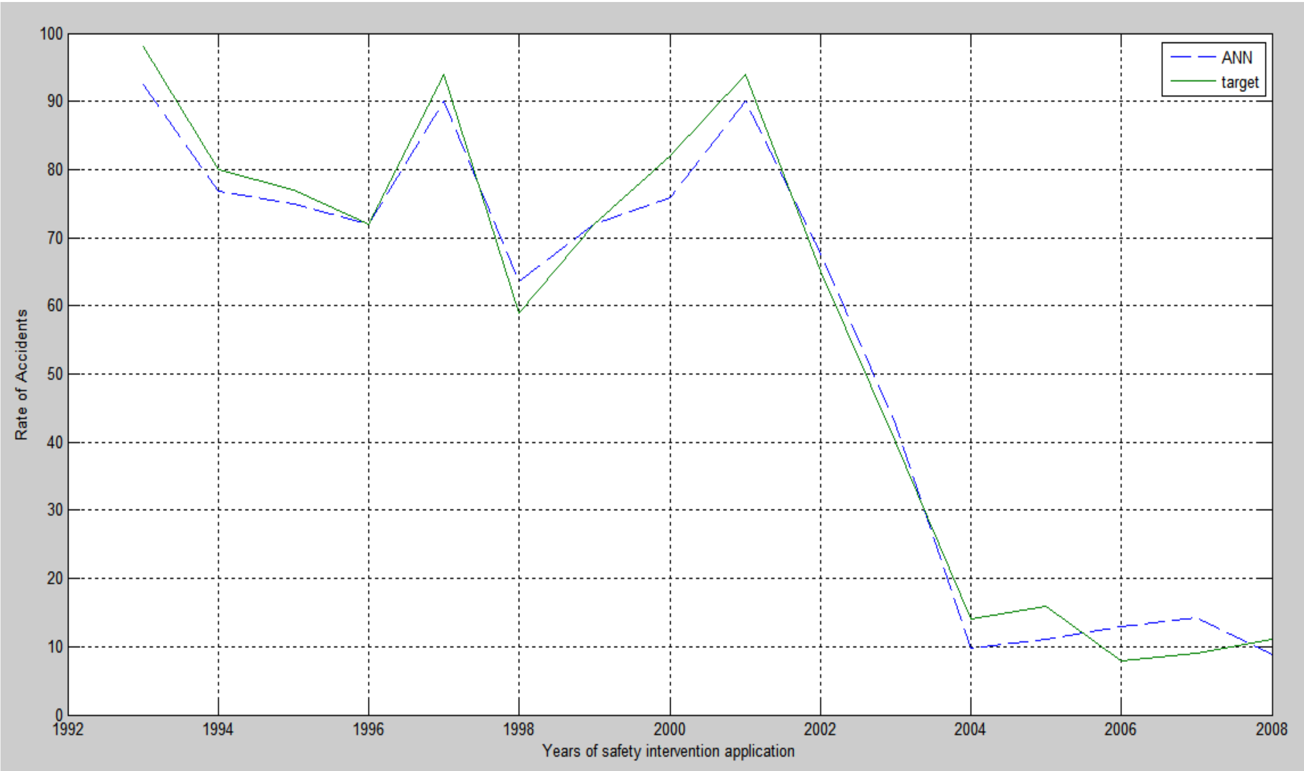

Figure 3: Comparison of Rate of Accidents between the Actual (Target) and Predicted Values for Combination ADEF

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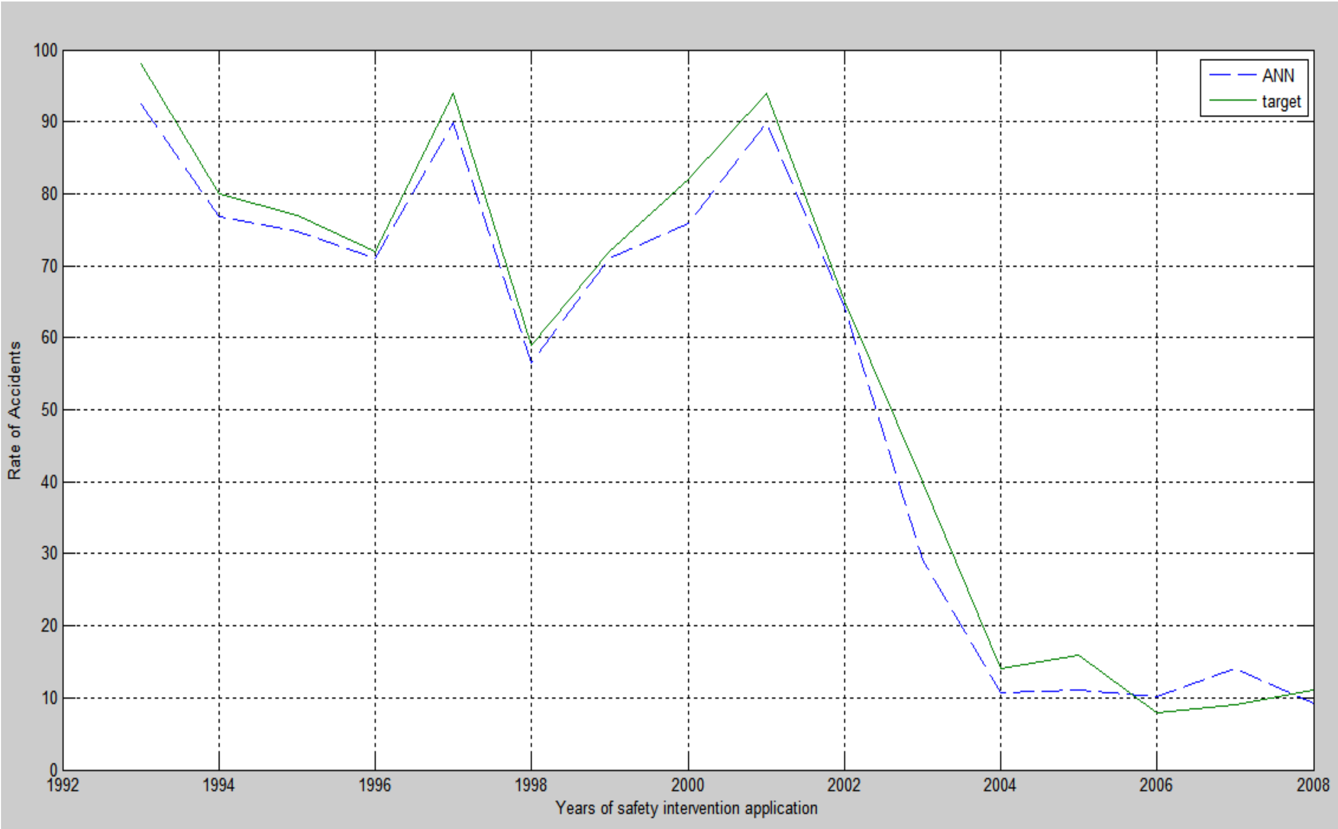

Figure 4: Comparison of Rate of Accidents between the Actual (Target) and Predicted Values for Combination ACDEF

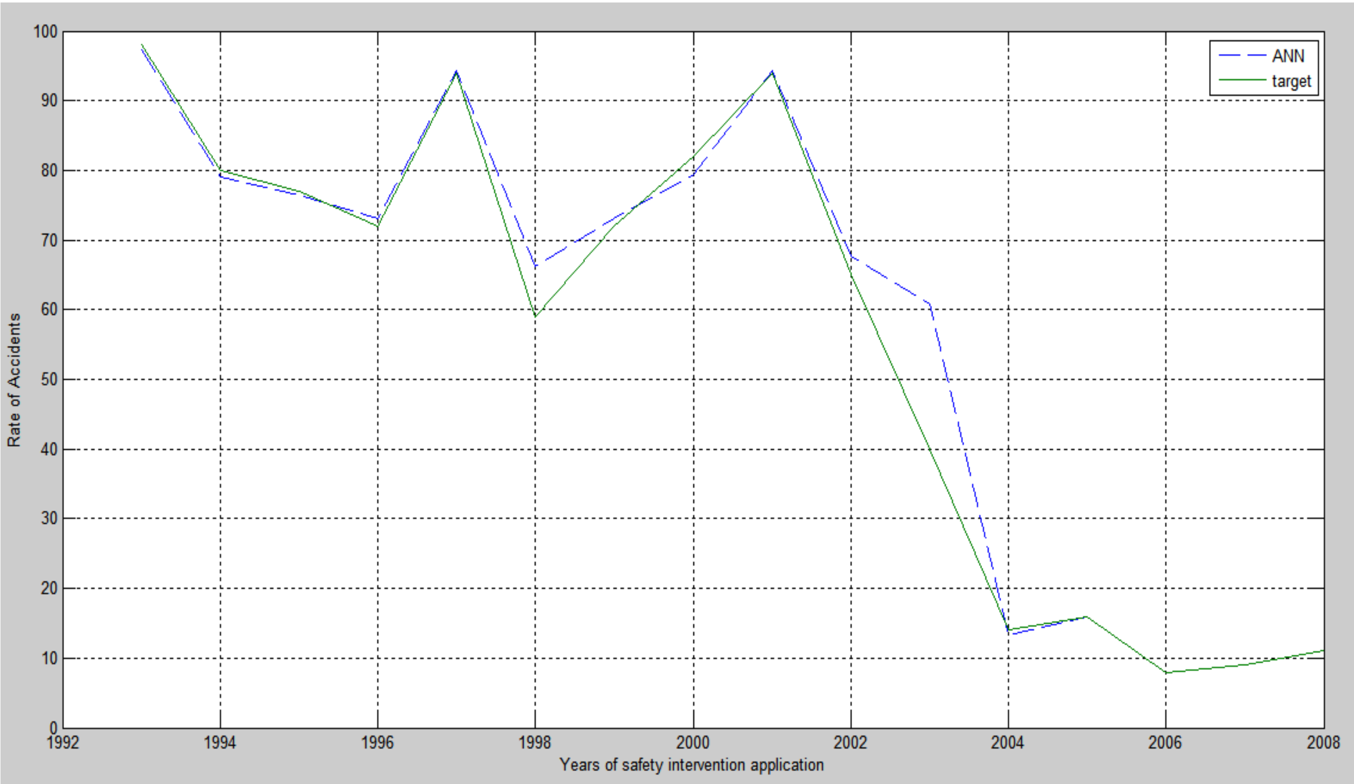

Figure 5: Comparison of Rate of Accidents between the Actual (Target) and Predicted Values for Combination ABDEF

5. CONCLUSIONS

Since safety interventions programmes (SIP) are mostly perceived as being costly and expensive, safety managers are thus left with meeting the daunting challenges of the cost implication. This research work investigates the possibilities of various combinations of prevention activities. Without any doubt, it is clear from this study that the combinations of the six factors at a time will produce the best safety result but in the face of scarce resources, the safety manager can still be able to come up with the best mix of factors that can produce a better safety result. Thus, ANN serves a better tool for planning and managing manufacturing safety programme.

With the relatively minimal MSE value of combinations containing SIP-F and its absence in other combinations gave a very high MSE value, it shows that SIP-F (Training) is the most important of the six interventions. Nevertheless, the order of the relative importance of these safety interventions programmes can be arranged as: Training, Awareness Creation, Personal Protective Equipment, Guarding, Accident Investigation, and Motivation of workers.

REFERENCES

[1] Adebiyi K. A., Charles-Owaba O.E. and Waheed M.A. (2007) Safety performance evaluation models: a review. *Disaster Prevention and Management, an International Journal*, 16, 2, 178 – 187

[2] Pedersen L. M., Nielsen K. J. and Kines P. (2012) Realistic evaluation as a new way to design and evaluate occupational safety interventions. Safety Science. 50. 48–54

[3] Perez-Floriano L. R. and Gonzalez J. A. (2007) Risk, safety and culture in Brazil and Argentina: the case of TransInc Corporation. *International Journal of Manpower* 28. 5. 403-417.

[4] Adebiyi K. A. (2006). The Development of Manufacturing Safety Programme Simulator. Unpublished PhD Thesis. Industrial Engineering Department, Faculty of Engineering, University of Ibadan, Ibadan.

[5] Law W.K., Chan A.H.S. and Pun K.F. (2006). Prioritising the safety management elements A hierarchical analysis for manufacturing enterprises. *Industrial Management & Data Systems*. 106. 6. 778-792.

[6] Demuth, H., Beale, M. and Hagan M., (2009), "Neural network toolbox user's guide, Matlab user's guide", Natick M.A, The mathworks Inc.