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Full Length Research Paper

A committee machine approach to multiple response optimization

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Multiple responses optimization problems have three phases including design of experiments, modeling and optimization. Artificial neural networks and genetic algorithm are applied for second and third phases. Committee machines include some experts such as some neural networks which operate together to get response. Current article applies a committee machine including four different artificial neural networks to model multiple responses optimization problems. Genetic algorithm is applied to calculate weights of committee machine and also it optimizes desirability function of all responses to get optimum point. Seven different cases in multiple responses optimization were modeled and analyzed. The results show the error of committee machine is near half of average error of artificial neural networks and global desirability of committee machine is the same as average global desirability of artificial neural networks.

Key words: Committee machines, multiple responses optimization, genetic algorithm, neural networks.

INTRODUCTION

The subject of multiple response optimization (MRO) is to find a set of input variable amounts (x's) to achieve a desired set of outputs (y's).

Usually MRO is done in three phases including experiments design, modeling and optimization. Modeling as second phase, is a potential field to achieve superior responses. Usually mathematical functions or artificial neural networks (ANNs) are applied for modeling in this phase. Committee machine (CM) or committee neural network is a special neural network which could be applied to MRO modeling. This article is an effort to implement CM and genetic algorithm (GA) to solve some MRO problems. The results show CM yields superior responses to individual ANNs.

Experiments design is arranged based on some known patterns in design of experiments (DOE) knowledge such as factorial design, fraction factorial design. Some deigns in response surface methodology (RSM) such as central composite design (CCD) and Box Behnken (Del Castillo et al., 1996; Guo et al., 2010). Also, Taguchi orthogonal arrays (Antony et al., 2006; Chang, 2008; Kumanan et al., 2007; Yao et al., 2008) which is derived from Taguchi method.

Second phase is done by means of different mathematical or statistical modeling such as multiple linear and nonlinear regression in the form of polynomials (Del Castillo et al., 1996; Lepadatu et al., 2005; Pasandideh and Niaki, 2006) and Artificial Neural Networks (ANNs). Due to the fact that relationship between inputs and outputs usually are complicated, ANNs mostly are used for modeling rather than polynomials. A typical Artificial Neural Network (ANN) is back propagation neural network (BPNN) that is used in many engineering problems (Mukherjee and Ray, 2008; Noorossana et al., 2008). Cheng et al. (2002) used MANFIS (Multi Adaptive Neuro Fuzzy Inference System) for modeling and showed the results are superior to RSM polynomial models.

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Last phase is optimization which usually is done on global desirability function. In this process, every predicted response is converted to a value between 0 and 1 by a function with name desirability function. So for all responses, a combination function is defined which converts all desirability functions to a unique number by global desirability function (GDF). Then with optimization of GDF, optimum or optimal values of independent parameters could be found. Different optimization techniques were used to optimize GDF, for example Excel solver, search methods such as Hook and Jeeves (Del Castillo et al., 1996), Evolutionary Algorithms such as Genetic algorithm (Pasandideh and Niaki, 2006; Noorossana et al., 2008) and Tabu Search (Mukherjee and Ray, 2008). Also, Chatsirirungruang and Miyakawa (2009) proposed a combination of GA with Taguchi and have used benefits of these techniques together to get more accurate responses.

ARTIFICIAL NEURAL NETWORKS AND COMMITTEE MACHINE

There are different kinds of neural networks to model and apply in complicated prediction problems. This study has considered four neural networks. They are Feed Forward Neural Networks, Radial Basis function networks Generalized Regression also, Adaptive Neural Fuzzy Inference System (ANFIS).

Feed Forward Neural Networks include one input layer, one output layer and one or some hidden layers (Kamo and Dagli, 2009). Radial basis neural network or Radial basis function neural network (RBFN) includes three layers, input layer for feeding the feature vectors into the network, a hidden layer of radial basis function neurons for calculating the outcome of the biases functions and a layer of output neurons for calculating a linear combination of the biases functions (Celikoglu, 2006). A generalized regression neural network (GRNN) is often used for function approximation (Matlab User's Guide, 2010). A fuzzy inference system (FIS) is defined as a way of mapping an input space to an output space using fuzzy logic (Ardil and Sandhu, 2010). Adaptive Neuro Fuzzy Inference System (ANFIS) is a kind of adaptive fuzzy inference system which employs a hybrid-learning algorithm to determine fuzzy system parameters automatically (Bo et al., 2009).

Nowadays, the problems with more volume and complexity data are growing rapidly and so the tools to solve these problems have to be more efficient and powerful. This can be done by applying different techniques such as soft approximation (Feng et al., 2011) and also new techniques in neural networks such as committee machines. A Committee Machine (CM) consists of a group of intelligent systems named Experts, and a combiner which combines the outputs of each expert (Figure 1). Its advantages are that it reaps the benefits of all work with only little additional computation.

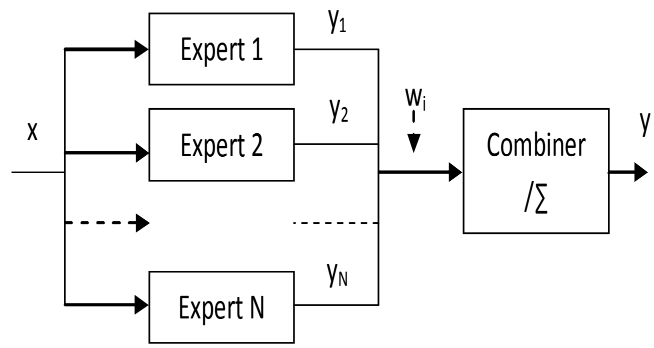

Figure 1. A typical architecture of a committee machine based on static structure.

Inputs are entered to experts, and all experts' responses are transferred to a combiner to get final response. To combine the experts' outputs, there are different ways in the combiner. It could be an intelligent system such as a neural network. The most popular method is the simple ensemble averaging method according to Equation 1 (Ismail et al., 2010).

$$y = \sum_{i=1}^{N} w_{i.} y_i \qquad (1)$$

where N is the total number of the experts used, wi is the weight coefficient of expert ith and yi is the estimated response from expert ith (Kadkhodaie-Ilkhchi et al., 2009).

Genetic Algorithm could be obtained by combination of the experts' contribution (weights) in a committee machine. Equation 2 represents committee machine gives smaller errors than the average of all the experts (Kadkhodaie-Ilkhchi et al., 2009; Karimpouli et al., 2010).

$$\mathrm{Error}_{CM} = \xi\left[\frac{1}{N}\sum_{i=1}^{N} e_i^{\,2}\right] \leq \frac{1}{N}\sum_{i=1}^{N} \xi[e_i^{\,2}] = \mathrm{Error}_{ave} \qquad (2)$$

$e_i = y_{i\_ANN} - y_{i\_real}$ is error of predicted and real response of every ANN or expert. $e_i^{\,2}$ is squared error for the ith expert. Error_{ave} is the average error for each of the experts acting alone. Error_{CM} is error of CM.

GENETIC ALGORITHM AND GLOBAL DESIRABILITY

Genetic Algorithm (GA) can quickly and reliably solve problems that are difficult to tackle by traditional methods. It is extensible and can interface with existing models and hybridize with them (Liang, 2008). GA works according to selection of the initial population. Then algorithm starts to evaluate the fitness function and select the best ones, it applies genetic operations such as mutation and crossover to reproduce new individuals and repeats evaluation and reproduction to get best population that it is optimal response (Tian and Noore, 2005).

Global desirability function is used to convert a problem of multiple responses into a single response case. By desirability function, each estimated response is transformed into a dimensionless desirability value di. For different situations, di values are defined by the following continuous function (Benyounis et al., 2008; Chang and Chen, 2011).

For goal of target, the desirability is defined by:

$$d_i(y_i) = \begin{cases} 0 & y_i \le L_i \\ \left(\frac{y_i - L_i}{T_i - L_i}\right)^s & L_i \le y_i \le T_i \\ \left(\frac{y_i - U_i}{T_i - U_i}\right)^t & T_i \le yi \le U_i \\ 0 & y_i \ge U_i \end{cases} \quad (3)$$

For goal of maximum, the desirability is defined by

$$d_i(y_i) = \begin{cases} 0 & y_i \le L_i \\ \left(\frac{y_i - L_i}{U_i - L_i}\right)^s & L_i \le y_i \le U_i \\ 1 & y_i \ge U_i \end{cases}$$

For goal of minimum, the desirability is defined by

$$d_i(y_i) = \begin{cases} 1 & y_i \le L_i \\ \left(\frac{U_i - y_i}{U_i - L_i}\right)^s & L_i < y_i < U_i \\ 0 & y_i \ge U_i \end{cases} \quad (5)$$

For goal In range, the desirability is defined by (6)

$$d_i(y_i) = \begin{cases} 1 & L_i \le y_i \le T_i \\ 0 & \text{Otherwise} \end{cases}$$

s and t are coefficient of convexity and determine how strictly target value will be desired. In current study they are equal to one. Combination of d_i's for same x's will yield "Global Desirability" (GD). Usually this global desirability function formula is:

$$GD = \sqrt[N]{\prod_{j=1}^{N} d_j} \quad (7)$$

Dependent to the problem, every response desirability is calculated by means of equations of 3 to 6, all desirabilities are entered to Equation 7, and finally GD is calculated. The d_i's range varies from zero to one, and respectively global desirability rang is from 0 to 1. Important notice is that optimization of GD is concerned to all desirabilities and thus denoted as simultaneous optimization of all responses. Current study introduces application of CM in MRO. Also GA is applied both in modeling and optimization phases. GA Fitness function in modeling phase is root mean square error and it is GD in optimization phase.

METHODOLOGY

The base of selection of training data sets was Dixit and Chandra suggestion (Dixit and Chandra, 2003) which expresses for n input, the minimum number of training set should be such that it encompasses the corners of n-dimensional space with to respect more contribution for input variables with more influence on output. But this suggestion was applied for corners of lower and upper limits for all responses. Number of training data sets was 80° of all data number.

There are different criteria to evaluate forecasting models performance. In the current study three criteria were selected to compare simulated results from models and the observed or real data. They are root mean square error (RMSE), mean absolute error (MAE) (Haghizadeh et al., 2010) and correlation coefficient (R) (Krause et al., 2005).

$$RMSE = \sqrt{\left(\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2\right)} \quad (8)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} abs(y_i - \hat{y}_i) \quad (9)$$

$$R = \frac{\sum_{i=1}^{N}(y_i - \bar{y}_i).(\hat{y}_i - \bar{\hat{y}}_i)}{\sqrt{\left(\sum_{i=1}^{N}(y_i - \bar{y}_i)^2.(\hat{y}_i - \bar{\hat{y}}_i)^2\right)}} \quad (10)$$

$-1 \le R \le +1$

y_i is the ith actual value, $\hat{y}_i$ is ith predicted value (model output) and n is the number of data used for prediction. Also $\bar{y}$ and $\bar{\hat{y}}$ are the mean of actual and predicted values. The first criterion measures the average error for all points. Smaller values of RMSE indicate higher accuracy in prediction and also coefficient of determination measures the accuracy of prediction of the model (Banik et al., 2009). There are two conditions to build ANNs model in the current study. The first condition is that RMSE for all data is minimum. The second condition is that correlation coefficient of testing data is positive.

As it is mentioned, MRO solution includes three phases. First, experiments design phase which in the current work, all data is selected from literatures. Second, modeling which is done by building four different neural networks including feed forward, RBF, GRNN and one ANFIS models. All ANNs have same inputs and one output and so the number of ANNs in every model is equal to the number of responses (Figure 2).

Figure 2. Input and outputs of every model.

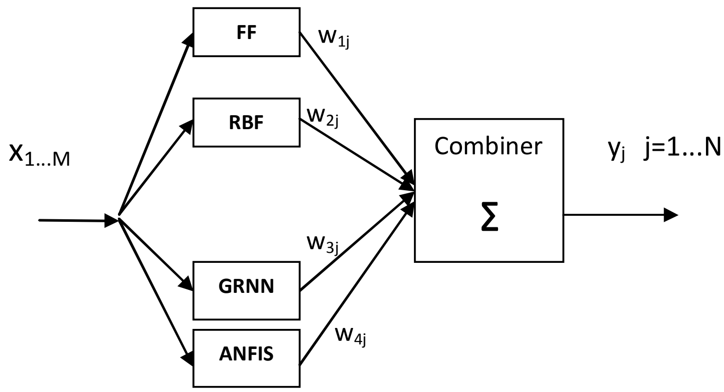

Figure 3. Committee machine architecture.

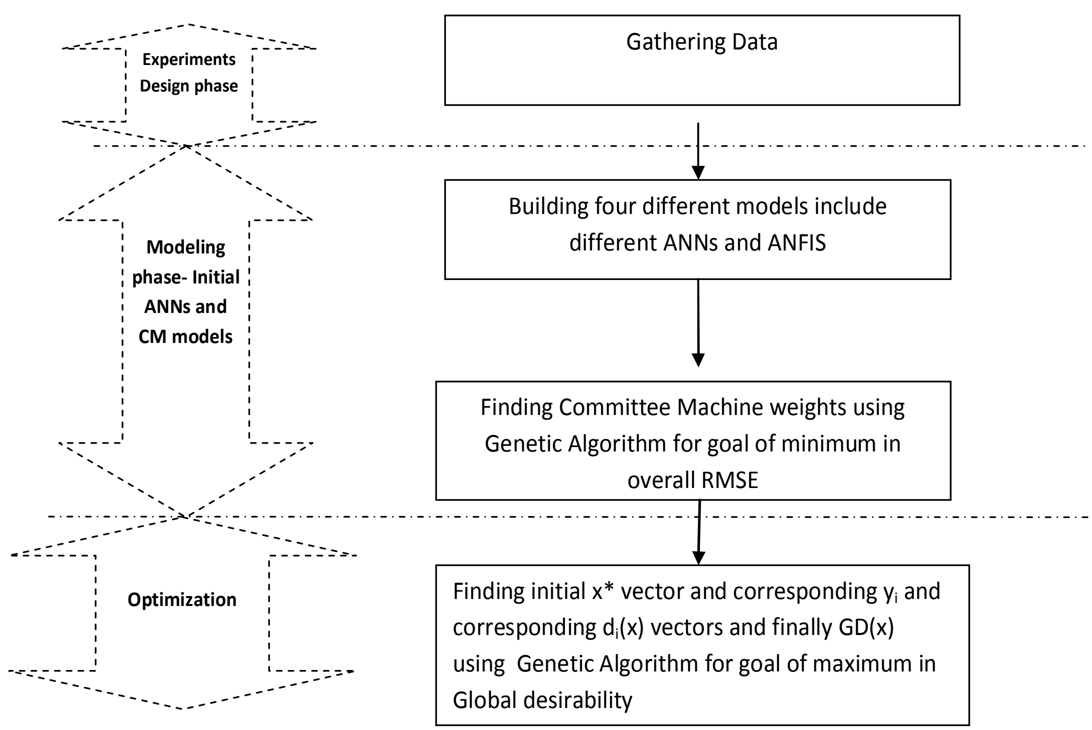

Figure 4. Methodology schematic to solve MRO by CM and GA.

A committee machine (CM) was constructed by combination of all four models (Figure 3). M Inputs are entered to every expert of CM simultaneously, and N responses are multiplied to their weights and then are added together to get final response. CM combiner is an ensemble averaging. CM weights were determined by Genetic Algorithm with the object to minimize RMSE of CM response (Fi. So CM weights will be a M*N matrix.

Schematic of methodology is shown in Figure 4, also pseudo

Table 1. GA Specification.

Variable	Magnitude/kind	Variable	Magnitude/kind
Parent population	20	Mutation type	Uniform
Selection function	Stochastic uniform	Number of variables	5
Number of elites	2	Number of responses	1
Crossover fraction	0.8	Migration direction	'Forward'
Crossover function	Scattered	Migration fraction	0.2

Table 2. Cases properties.

Case no.	No. of x's	No. of y's	No. of experiment	Reference
1	3	6	15	Noorossana et al., 2008
2	6	3	52	Rajakumar et al., 2011
3	4	2	18	Giordano et al., 2010
4	3	3	30	Martinez et al., 2009
5	2	2	13	Bhatti et al., 2011
6	3	3	20	Benyounis et al., 2008
7	4	4	30	Aggarwala et al., 2008

code is as follow:

```
get Data //include X,Y matrixes
set RMSE_network =1                    // beginning of modeling phase
set min_RMSE=0.4
for all kind of neural networks
while (RMSE_network >min_RMSE or coefficient of correlation<0) and iterations<50
set X and Y randomly
train network
calculate RMSE_network and coefficient of correlation
if RMSE_network < min_RMSE
set  min_RMSE=RMSE_network
end if
add one to iterations
end                          // end of while
end for
calculate CM weights using GA for goal of minimum in overall RMSE      // end of modeling phase
calculate X* using GA for goal of maximum in Global desirability
//
```

RESULTS AND DISCUSSION

Genetic algorithm is used in two steps. First to find CM weights with object of minimizing the overall RMSE of CM and second to find x's by GA and ANNs with object of maximizing global desirability. For all of them, GA specifications are as Table 1.

Seven MRO problems were selected to solve with CM. these problems include different number of inputs and outputs, also different number of experiments. Their properties are shown in Table 2.

Case 1

The problem is based over the wire-bonding process in the semiconductor industry. During this process, the manufacturer should assemble a hybrid module in a pre-molded package by bonding wires between the leads. The input and output variable are listed in Table 3. Different neural networks were made to model data of experiments. These ANNs specifications are listed in Table 4.

To have better comparison between committee machine and other neural networks, same specifications were considered for all other cases as Table 5 except Case 4, and that was due to get acceptable results.

Four ANNs include feedforward, Radial Base Function, GRNN and ANFIS were consisted for every response for every problem data. So every problem found 24 models. Consequently, the results of every model are according to Table 6.

A committee machine was made with object to minimize overall RMSE and CM's weights are according to Table 7. In addition, Table 8 shows CM and ANNs results and minimum and average of ANNs results.

Case 2

The target is to get amounts of quantitative characteristics of the friction stir welded AA6061-T_6 aluminium alloy in the welding process. The input and output variable are listed in Table 9.

Different neural networks were made to model data of

Table 3. Input and response variables and optimization criteria for every response (output) in Case 1.

Input (Independent) variable	Output (Dependent) variable	Opt. criteria
x1: Flow rate (SCFM)	y1: Maximum temperature at position A (℃)	Target
x2: Flow temp (℃)	y2: Beginning bond temperature at position A (℃)	Target
x3: Block temp (℃)	y3: Finish bond temperature at position A (℃)	Target
	y4: Maximum temperature at position B (℃)	Target
	y5: Beginning bond temperature at position B (℃)	Target
	y6: Finish bond temperature at position B (℃)	Target

Table 4. Networks specifications for Case 1.

Response	No. of neurons in hidden and output layer of feed forward	RBF spread coefficient	GRNN spread coefficient	ANFIS membership function
y1	3-6-1	0.75	0.55	dsigmf
y2	3-6-1	0.75	0.67	trimf
y3	3-4-1	0.9	0.67	trimf
y4	3-3-1	0.45	0.6	trimf
y5	3-6-1	0.9	0.65	gbellmf
y6	3-3-1	0.66	0.65	gbellmf

Table 5. Networks specifications for cases 2-7 for all y's.

Case no.	No. of neurons in hidden and output layer of feed forward	RBF spread coefficient	GRNN spread coefficient	ANFIS membership function
2,3,5,6,7	3-1	0.85	0.5	gbellmf
4	3-5-1	0.85	0.45	gbellmf

Table 6. RMSE and R for training, testing and all data in cases of normalized and real (Case 1).

Model	RMSE_N train	RMSE_N test	RMSE_N all	R train	R test	R all	RMSE r_train	RMSE r_test	RMSE r_all
FF_y4	0.106	0.111	0.107	0.971	0.979	0.981	0.106	0.111	0.107
FF_y5	0.074	0.023	0.067	0.990	1.000	0.992	2.858	0.867	2.585
FF_y6	0.060	0.096	0.069	0.990	0.971	0.992	2.450	3.880	2.795
FF_y7	0.028	0.086	0.046	0.999	0.999	0.998	1.225	3.834	2.035
FF_y8	0.017	0.017	0.017	1.000	1.000	1.000	0.612	0.644	0.619
FF_y9	0.030	0.053	0.036	0.999	0.982	0.998	1.349	2.360	1.603
RBF_y4	0.094	0.096	0.095	0.988	0.850	0.986	3.682	3.734	3.692
RBF_y5	0.074	0.103	0.081	0.992	0.921	0.989	2.858	3.964	3.111
RBF_y6	0.060	0.059	0.060	0.994	0.999	0.993	2.450	2.385	2.437
RBF_y7	0.028	0.078	0.043	0.999	0.991	0.998	1.225	3.492	1.908
RBF_y8	0.017	0.032	0.021	1.000	0.999	0.999	0.612	1.183	0.762
RBF_y9	0.018	0.082	0.040	0.999	0.937	0.997	0.817	3.670	1.797
GRNN_y4	0.098	0.014	0.088	0.988	0.977	0.988	3.823	0.531	3.428
GRNN_y5	0.112	0.033	0.101	0.991	0.999	0.991	4.314	1.265	3.900
GRNN_y6	0.095	0.118	0.100	0.997	0.916	0.992	3.844	4.793	4.052
GRNN_y7	0.045	0.078	0.053	0.999	0.982	0.998	1.998	3.476	2.368
GRNN_y8	0.060	0.074	0.063	0.999	0.971	0.998	2.237	2.737	2.345
GRNN_y9	0.056	0.068	0.059	1.000	0.975	0.998	2.506	3.041	2.622

Table 6. Contd.

ANFIS_y4	0.094	0.092	0.094	0.986	0.992	0.986	3.674	3.590	3.658
ANFIS_y5	0.074	0.117	0.085	0.992	0.964	0.988	2.858	4.508	3.255
ANFIS_y6	0.060	0.062	0.061	0.994	0.974	0.993	2.450	2.503	2.460
ANFIS_y7	0.028	0.066	0.038	0.999	0.981	0.998	1.225	2.932	1.709
ANFIS_y8	0.017	0.027	0.019	1.000	0.999	0.999	0.612	0.986	0.703
ANFIS_y9	0.018	0.025	0.020	0.999	0.998	0.999	0.817	1.134	0.889

Table 7. Committee machines weights by GA (Case 1).

Model	y1	y2	y3	y4	y5	y6
FF	0.0121	1.0000	0.0768	0.0019	0.4402	0.1567
RBF	0.5377	0.0000	0.3966	0.2612	0.0145	0.0400
GRNN	0.0405	0.0000	0.0000	0.0034	0.0007	0.1210
ANFIS	0.4097	0.0000	0.5266	0.7335	0.5447	0.6823

Table 8. CM and its experts results (Case 1).

Model	GD	Overall RMSE	Overall MAE
FF	0.444	2.55	1.31
RBF	0.000	2.47	1.12
GRNN	0.000	3.20	2.45
ANFIS	0.617	2.39	1.04
average	0.530	2.65	1.48
CM	0.594	2.15	0.96

Table 9. Input and response variables and optimization criteria for every response (output) (Case 2).

Input (Independent) variable	Output(Dependent) variable	Opt. criteria
x1: Rotational speed (rpm)	y1: Tensile strength (MPa)	Maximize
x2: Welding speed (mm/min)	y2: Hardness (HV)	Maximize
x3: Axial force (kN)	y3: Corrosion rate (mm/y)	In range
x4: Shoulder diameter (mm)		
x5: Pin diameter (mm)		
x6: Tool hardness (HRc)		

experiments. These ANNs specifications are listed in Table 5. Consequently, the results of every model are according to Table 10. A committee machine was made with object to minimize overall RMSE and CM's weights are as Table 11.

Table 12 shows CM and ANNs results and minimum and average of ANNs results.

Case 3

The problem is to optimize the yield of recombinant *Oryza sativa* non-symbiotic hemoglobin 1 in medium containing byproduct glycerol. The input and output variable are listed in Table 13.

Different neural networks were made to model data of experiments. These ANNs specifications are listed in Table 5. After modeling, the results of every model are according to Table 14.

A committee machine was made with object to minimize overall RMSE and CM's weights as shown in Table 15.

Table 16 shows CM and ANNs results and minimum and average of ANNs results.

Table 10. RMSE and correlation coef. (R) for training, testing and all data in case of normalized (case 2).

Model	RMSE N_train	RMSE N_test	RMSE N_all	R train	R test	R all
FF_y1	0.109	0.227	0.140	0.976	0.665	0.956
FF_y2	0.049	0.112	0.066	0.996	0.960	0.993
FF_y3	0.219	0.226	0.220	0.928	0.848	0.916
RBF_y1	0.031	0.109	0.055	0.998	0.923	0.993
RBF_y2	0.016	0.072	0.035	1.000	0.958	0.998
RBF_y3	0.147	0.232	0.167	0.969	0.652	0.953
GRNN_y1	0.282	0.371	0.301	0.997	0.862	0.957
GRNN_y2	0.328	0.455	0.356	0.999	0.862	0.949
GRNN_y3	0.347	0.368	0.351	0.966	0.441	0.936
ANFIS_y1	0.031	0.532	0.235	0.998	0.366	0.893
ANFIS_y2	0.016	0.684	0.300	1.000	0.734	0.881
ANFIS_y3	0.147	0.558	0.278	0.968	0.105	0.874

Table 11. Committee machines weights by GA (Case 2).

Model	y1	y2	y3
FF	0.0255	0.1943	0.2173
RBF	0.9201	0.7616	0.6599
GRNN	0.0127	0.0098	0.0051
ANFIS	0.0418	0.0343	0.1177

Table 12. CM and its experts results (case 2).

Model	GD	Overall RMSE	Overall MAE
FF	0.998	2.78	1.79
RBF	0.957	1.20	0.51
GRNN	0.899	8.55	6.63
ANFIS	0.977	7.01	2.31
average	0.958	4.88	2.81
CM	0.976	1.18	0.67

Table 13. Input and response variables and optimization criteria for every response (output) (Case 3).

Input (Independent) variable	Output(dependent) variable	Opt. criteria
x1: Tryptone. (g L^{-1})	y1: Biomass (g L^{-1})	Minimize
x2: Yeast extract (g L^{-1}) x3: Sodium chloride (g L^{-1}) x4: Byproduct glycerol (g L^{-1})	y2: Oryza sativa non-symbiotic hemoglobin1_ OsHb1 (g L^{-1})	Maximize

Case 4

The problem is multiple response optimization of styrene–butadiene rubber (SBR) emulsion batch polymerization. The input and output variable are listed in Table 17.

Different neural networks were made to model data of experiments. These ANNs specifications are listed in Table 5. After modeling, the results of every model are according to Table 18. A CM was made with object to minimize overall RMSE and CM's weights are as Table 19. Table 20 shows CM and ANNs results and minimum

Table 14. RMSE and correlation coefficient (R) for training, testing and all data in case of normalized (Case 3).

Model	RMSE N_train	RMSE N_test	RMSE N_all	R train	R test	R all
FF_y1	0.104	0.219	0.138	0.982	0.919	0.968
FF_y2	0.112	0.218	0.143	0.981	0.642	0.968
RBF_y1	0.015	0.202	0.096	1.000	0.964	0.985
RBF_y2	0.002	0.238	0.112	1.000	0.854	0.981
GRNN_y1	0.087	0.163	0.109	0.998	0.983	0.990
GRNN_y2	0.125	0.304	0.181	0.999	0.813	0.969
ANFIS_y1	0.015	0.210	0.100	1.000	0.852	0.984
ANFIS_y2	0.002	0.230	0.108	1.000	0.944	0.982

Table 15. Committee machines weights by GA (Case 3).

Model	y1	y2
FF	0.1181	0.2043
RBF	0.3471	0.3423
GRNN	0.2336	0.0048
ANFIS	0.3012	0.4486

Table 16. CM and its Experts results (case 3).

Model	GD	Overall RMSE	Overall MAE
FF	0.707	0.67	0.38
RBF	0.694	0.47	0.18
GRNN	0.582	0.56	0.42
ANFIS	0.708	0.48	0.20
Average	0.673	0.54	0.30
CM	0.678	0.29	0.22

Table 17. Input and response variables and optimization criteria for every response (output) (Case 4).

Input (Independent) Variables	Output (Dependent) Variables	Opt. criteria
Initiator (ml)	Solid content of latex (wt%)	Target
Activator (ml)	Mooney viscosity	Target
Chain transfer agent_CTA (ml)	Polydispersity	Target

and average of ANNs results.

Case 5

Object of this case is to optimize process variables, electrolysis voltage and treatment time for the electro coagulation removal of hexavalent chromium (Cr(VI)). The input and output variable are listed in Table 21. Different neural networks were made to model data of experiments. These ANNs specifications are listed in Table 5. After modeling, the results of every model are according to Table 22. A committee machine was made with object to minimize overall RMSE and CM's weights are as Table 23.

Table 24 shows CM and ANNs results and minimum and average of ANNs results.

Case 6

In this case mechanical properties of laser-welded butt

Table 18. RMSE and correlation coef.(R) for training, testing and all data in case of normalized (Case 4).

Model	RMSE N_train	RMSE N_test	RMSE N_all	R train	R test	R all
FF_y1	0.103	0.238	0.141	0.988	0.923	0.976
FF_y2	0.255	0.288	0.262	0.908	0.830	0.893
FF_y3	0.181	0.369	0.231	0.936	0.776	0.897
RBF_y1	0.000	0.286	0.128	1.000	0.670	0.983
RBF_y2	0.000	0.307	0.137	1.000	0.675	0.973
RBF_y3	0.000	0.556	0.249	1.000	0.219	0.878
GRNN_y1	0.203	0.114	0.189	0.957	0.990	0.958
GRNN_y2	0.396	0.196	0.365	0.899	0.496	0.886
GRNN_y3	0.379	0.376	0.378	0.766	0.344	0.707
ANFIS_y1	0.000	0.320	0.143	1.000	0.974	0.979
ANFIS_y2	0.007	0.407	0.182	1.000	0.334	0.952
ANFIS_y3	0.005	0.845	0.378	1.000	0.285	0.772

Table 19. Committee machines weights by GA (Case 4).

Model	y1	y2	y3
FF	0.0078	0.0773	0.0188
RBF	0.9678	0.3608	0.8409
GRNN	0.0034	0.0197	0.0003
ANFIS	0.0210	0.5423	0.1400

Table 20. CM and its experts results (Case 4).

Model	GD	Overall RMSE	Overall MAE
FF	0.985	10.54	4.74
RBF	1.000	5.54	1.25
GRNN	0.905	14.70	7.28
ANFIS	0.997	7.34	1.82
Average	0.972	9.53	3.77
CM	0.976	4.22	1.38

Table 21. Input and response variables and optimization criteria for every response (output) (Case 5).

Input (Independent) variable	Output (Dependent) variable	Opt. criteria
x1: Voltage(V)	y1: Reduction efficiency (%)	Maximize
x2: Time (min)	y2: Energy consumption (Wh)	Minimize

joints made of AISI304 were investigated to obtain good welded joints. The input and output variable are listed in Table 25.

Different neural networks were made to model data of experiments. These ANNs specifications are listed in Table 5. After modeling, the results of every model are according to Table 26.

A committee machine was made with object to minimize overall RMSE and CM's weights are as Table 27.

Table 28 shows CM and ANNs results and minimum and average of ANNs results.

Case 7

Problem is to optimize multiple characteristics in CNC turning of AISI P-20 tool steel using liquid nitrogen as a coolant. The input and output variable are listed in Table

Table 22. RMSE and correlation coef.(R) for training and testing and all data in case of normalized (Case 5).

Model	RMSE N_train	RMSE N_test	RMSE N_all	R train	R test	Ro all
FF_y1	0.046	0.080	0.055	0.997	0.997	0.997
FF_y2	0.017	0.016	0.017	1.000	1.000	1.000
RBF_y1	0.038	0.086	0.053	0.998	0.995	0.997
RBF_y2	0.002	0.037	0.018	1.000	0.991	1.000
GRNN_y1	0.164	0.141	0.159	0.995	0.998	0.994
GRNN_y2	0.159	0.132	0.153	0.997	0.998	0.996
ANFIS_y1	0.046	0.375	0.185	0.998	0.990	0.966
ANFIS_y2	0.016	0.011	0.015	1.000	0.995	1.000

Table 23. Committee machines weights by GA (Case 5).

Model	y1	y2
FF	0.4771	0.3008
RBF	0.4771	0.1156
GRNN	0.0003	0.0139
ANFIS	0.0455	0.5696

Table 24. CM and its experts results (Case 5).

Model	GD	Overall RMSE	Overall MAE
FF	0.876	0.46	0.28
RBF	0.853	0.45	0.24
GRNN	0.828	2.38	1.69
ANFIS	0.861	1.34	0.48
Average	0.854	1.16	0.67
CM	0.863	0.44	0.27

Table 25. Input and response variables and optimization criteria for every response (output) (Case 6).

Input (Independent) variable	Output (Dependent) variables	Opt. criteria
x1: Laser power (kW)	y1: Average tensile strength (Mpa)	Maximize
x2: Welding speed (cm/min)	y2: Average impact strength (J)	Maximize
x3: Focus position (mm)	y3: Joint cost (h/m)	In range

Table 26. RMSE and correlation coeffient (R) for training, testing and all data in case of normalized (Case 6).

Model	RMSE N_train	RMSE N_test	RMSE N_all	R train	R test	R all
FF_y1	0.152	0.155	0.153	0.963	0.856	0.959
FF_y2	0.082	0.057	0.078	0.985	0.985	0.985
FF_y3	0.002	0.001	0.002	1.000	1.000	1.000
RBF_y1	0.137	0.173	0.145	0.972	0.423	0.964
RBF_y2	0.071	0.081	0.073	0.988	0.995	0.987
RBF_y3	0.000	0.178	0.079	1.000	1.000	0.989
GRNN_y1	0.225	0.188	0.218	0.977	0.683	0.960
GRNN_y2	0.158	0.052	0.143	0.983	0.959	0.981
GRNN_y3	0.122	0.147	0.127	0.998	1.000	0.993

Table 26. Contd.

ANFIS_y1	0.159	0.507	0.267	0.964	0.446	0.888
ANFIS_y2	0.043	0.395	0.181	0.996	0.759	0.931
ANFIS_y3	0.000	0.112	0.050	1.000	0.963	0.994

Table 27. Committee machines weights by GA (case 6)

Model	y1	y2	y3
FF	0.3641	0.3283	0.9943
RBF	0.5876	0.6451	0.0001
GRNN	0.0325	0.024	0.0027
ANFIS	0.0158	0.0027	0.0029

Table 28. CM and its experts results (Case 6).

Model	GD	Overall RMSE	Overall MAE
FF	0.932	7.20	2.89
RBF	1.000	6.84	1.95
GRNN	0.903	10.29	4.57
ANFIS	0.951	12.62	4.66
Average	0.947	9.24	3.52
CM	0.917	6.78	2.33

Table 29. Input and response variables and optimization criteria for every response (output) (Case 7).

Input (Independent) variable	Output (Dependent) variable	Opt. criteria
Cutting speed (m/min)	Surface roughness (_m)	Minimize
Feed (mm/rev)	Tool life (min)	Maximize
Depth of cut (mm)	Cutting force (N)	Minimize
Nose radius (mm)	Power consumption (W)	Minimize

29. Different neural networks were made to model data of experiments. These ANNs specifications are listed in Table 5. After modeling, the results of every model are according to Table 30.

A committee machine was made with object to minimize overall RMSE and CM's weights are as Table 31. Table 32 shows CM and ANNs results and minimum and average of ANNs results.

Tables 33, 34 and 35 show comparison of the results between CM and average magnitudes of ANNs. Table 33 represents committee machine increases average global desirability about 0.1% or 0.001 corresponding to average GD of four neural networks. Consequently, there is a negligible change in global desirability due to the CM application.

Table 34 represents committee machine decreases average overall RMSE about 54% corresponding to average overall RMSE of four neural networks. Table 35 represents committee machine decreases average overall MAE about 49% corresponding to average overall MAE of four neural networks. Consequently, there is a decreasing about 50% in errors due to the CM application and this will yield a model with higher accuracy. Thus, using committee machine in multiple response optimization will cause a noticeable loss in errors, but this application does not have considerable change in global desirability.

Conclusion

There are different artificial neural networks (ANNs) for

Table 30. RMSE and correlation coefficient (R) for training, testing and all data in case of normalized (Case 7).

Model	RMSE N_train	RMSE N_test	RMSE N_all	R train	R test	R all
FF_y1	0.035	0.088	0.050	0.998	0.938	0.995
FF_y2	0.013	0.019	0.014	1.000	1.000	1.000
FF_y3	0.028	0.057	0.036	0.998	0.994	0.997
FF_y4	0.014	0.040	0.022	1.000	0.997	0.999
RBF_y1	0.020	0.160	0.074	0.999	0.323	0.989
RBF_y2	0.004	0.253	0.113	1.000	0.830	0.982
RBF_y3	0.006	0.143	0.064	1.000	0.534	0.991
RBF_y4	0.000	0.104	0.046	1.000	0.898	0.995
GRNN_y1	0.027	0.092	0.047	0.999	0.143	0.996
GRNN_y2	0.043	0.130	0.070	0.998	0.853	0.993
GRNN_y3	0.036	0.090	0.051	0.998	0.658	0.995
GRNN_y4	0.020	0.099	0.048	0.999	0.978	0.994
ANFIS_y1	0.010	0.073	0.034	1.000	0.979	0.998
ANFIS_y2	0.004	0.032	0.015	1.000	0.994	1.000
ANFIS_y3	0.005	0.050	0.023	1.000	0.996	0.999
ANFIS_y4	0.006	0.028	0.014	1.000	0.976	1.000

Table 31. Committee machines weights by GA (Case 7).

Model	y1	y2	y3	y4
FF	0.2381	0.5818	0.162	0.2977
RBF	0.0763	0.0147	0.12	0.0386
GRNN	0.1223	0.0715	0.1362	0.1443
ANFIS	0.5633	0.3321	0.5817	0.5194

Table 32. CM and its experts results (Case 7).

Model	GD	Overall RMSE	Overall MAE
FF	0.904	6.19	2.59
RBF	0.905	13.26	2.61
GRNN	0.901	13.53	3.54
ANFIS	0.907	3.93	1.07
Average	0.904	9.23	2.45
CM	0.888	3.83	1.62

Table 33. Global desirability comparison.

Model	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
Average GD of 4 models	0.530	0.958	0.673	0.972	0.854	0.947	0.904
GD of committee machine	0.59	0.976	0.678	0.976	0.863	0.929	0.888
		1.9%	0.8%	0.4%	1.0%	-1.9%	-1.8%
Average Global Desirability (Cases 2-7)				**0.1%**			

modeling of multiple response optimization (MRO) problems. Committee machine is a collection of several experts or elements such as ANNs. Mathematically it is proved every committee machine yields smaller errors than the average of all the experts. Current study, has considered four different ANNs and one committee machine to model seven different cases in MRO. In addition, genetic algorithm is applied to find committee

Table 34. RMSE comparison.

Model	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
Average RMSE of 4 models	2.65	4.88	0.54	9.53	1.16	9.24	9.23
RMSE of Committee machine	2.16	1.18	0.29	4.22	0.44	6.78	3.83
	-19%	-76%	-47%	-56%	-62%	-27%	-59%
Average Overall RMSE (Cases 2-7)					**-54%**		

Table 35. MAE comparison.

Model	Case1	Case2	Case3	Case4	Case5	Case6	Case7
Average MAE of 4 models	1.48	2.81	0.30	3.77	0.67	3.52	2.45
MAE of committee machine	0.94	0.67	0.22	1.38	0.27	2.33	1.62
	-37%	-76%	-27%	-64%	-60%	-34%	-34%
Average Overall MAE (Cases 2-7)					**-49%**		

machine weights and independent variables with maximum desirability. The results show the final responses of committee machine have the error about 50% in comparison with average error of ANNs, but committee machine have same global desirability with average global desirability of ANNs.

REFERENCES

Aggarwala A, Singh H, Kumar P, Singh M (2008). Optimization of multiple quality characteristics for CNC turning under cryogenic cutting environment using desirability function. J. Mater. Process. Technol., 205: 42–50.

Antony J, Anand RB, Kumar M, Tiwari MK (2006). Multiple response optimization using Taguchi methodology and neuro-fuzzy based model. J. Manu. Tech. Manage., 17(7): 908-925.

Ardil E, Sandhu PS (2010). A soft computing approach for modeling of severity of faults in software systems. Int. J. Phy. Sci., 5(2): 074-085.

Banik S, Anwer M, Khodadad Khan AFM (2009). Predictive Power of the Daily Bangladeshi Exchange Rate Series based on Markov Model, Neuro Fuzzy Model and Conditional Heteroskedastic Model. Series Predictive Power of the Daily Bangladeshi Exchange Rate Series based on Markov Model, Neuro Fuzzy Model and Conditional Heteroskedastic Model. City, pp. 303-308.

Benyounis KY, Olabi AG ,Hashmi MSJ (2008). Multi-response optimization of CO2 laser-welding process of austenitic stainless steel. Opt. Laser Technol., 40: 76-87.

Bhatti MS, Reddy AS, Kalia RK, Thukral AK (2011). Modeling and optimization of voltage and treatment time for electrocoagulation removal of hexavalent chromium. Desalination, 269: 157–162.

Bo J, Yuchun T, Yan-Qing Z (2009). Hybrid SVM-ANFIS for protein subcellular location prediction. Int. J. Comput. Intel. Bioinfo. Syst. Biol., 1(1): 59.

Celikoglu HB (2006). Application of radial basis function and generalized regression neural networks in non-linear utility function specification for travel mode choice modelling. Math. Comput. Modell., 44: 640–658.

Chang HH (2008). A data mining approach to dynamic multiple responses in Taguchi experimental design. Expert Syst. Appl., 35: 1095–1103.

Chang H-H, Chen Y-K (2011). Neuro-genetic approach to optimize parameter design of dynamic multiresponse experiments. Appl. Soft Comput., 11: 436–442.

Chatsirirungruang P, Miyakawa M (2009). Application of genetic algorithm to numerical experiment in robust parameter design for signal multi-response problem. Int. J. Management Sci. Eng. Management, 4(1): 49-59.

Cheng CB, Cheng C-J, Lee ES (2002). Neuro-Fuzzy and Genetic Algorithm in Multiple Response Optimization. Comput. Math. Appl., 44: 1503-1514.

Del Castillo E, Montgomery DC,Mccarviille DR (1996). Modified desirability function for multiple response optimization. J. Qual. Technol., 28(3): 337-345.

Dixit US, Chandra S (2003). A neural network based methodology for the prediction of roll force and roll torque in fuzzy form for cold flat rolling process. Int. J. Adv. Manuf. Technol., 22: 883–889.

Feng F, Liu X, Leoreanu-Fotea V,d YBJ (2011). Soft sets and soft rough sets. Information Sci., 181: 1125–1137.

Giordano PC, Martínez HD, Iglesias AA, Beccaria AJ,Goicoechea HC (2010). Application of response surface methodology and artificial neural networks for optimization of recombinant *Oryza sativa* non-symbiotic hemoglobin 1 production by *Escherichia coli* in medium containing byproduct glycerol. Bioresour. Technol., 101: 7537–7544.

Guo W-l, Zhang Y-b, Lu J-h, Jiang L-y, Teng L-r, Wang Y,Liang Y (2010). Optimization of fermentation medium for nisin production from *Lactococcus lactis* subsp. lactis using response surface methodology (RSM) combined with artificial neural network-genetic algorithm (ANN-GA). Afr. J. Biotechnol., 9(38): 6264-6272.

Haghizadeh A, Teang SI, Goudarzi E (2010). Estimation of Yield Sediment Using Artificial Neural Network at Basin Scale. Aust. J. Basic Appl. Sci., 4(7): 1668-1675.

Ismail N, Golestaneh SJ, Tang SH, Ariffin MKAM, Moslemi Naeini H, Rouhani D (2010). Modified committee neural networks for prediction of machine failure times. The 3rd national intelligent systems and information technology symposium (ISITS 2010), Universiti Putra Malaysia (UPM), Malaysia.

Kadkhodaie-Ilkhchi A, Rezaee MR, Rahimpour-Bonab H (2009). A committee neural network for prediction of normalized oil content from well log data: An example from South Pars Gas Field, Persian Gulf. J. Petroleum Sci. Eng., 65: 23-32.

Kamo T, Dagli C (2009). Hybrid approach to the Japanese candlestick method for financial forecasting. Expert Syst. Appl., 36: 5023-5030.

Karimpouli S, Fathianpour N, Roohi J (2010). A new approach to improve neural networks' algorithm in permeability prediction of petroleum reservoirs using supervised committee machine neural network (SCMNN). J. Petroleum Sci. Eng., 73: 227–232.

Krause P, Boyle DP, B¨ase F (2005). Comparison of different efficiency criteria for hydrological model assessment. Adv. Geosci., 5: 89–97.

Kumanan S, Dhas JER, Gowthaman K (2007). Determination of submergrd arc welding process parameters using taguchi method and regression analysis. Indian J. Eng. Mater. Sci., 12: 177-183.

Lepadatu D, Kobi A, Hambli R, Barreau A (2005). Lifetime Multiple Response Optimization of Metal Extrusion Die. RAMS 2005 IEEE.

Liang Y (2008). Combining neural networks and genetic algorithms for predicting the reliability of repairable systems. Int. J. Qual. Reli. Manage., 25(2): 201-210.
Martinez DG, Olivieri A, Boschetti CE (2009). Multiple response optimization of styrene–butadiene rubber emulsion polymerization. Comput. Chem. Eng., 33: 850–856.
Matlab User's Guide (2010). Version 2010b. Neural Network Toolbox. Math Works,USA.
Mukherjee I, Ray PK (2008). A modified tabu search strategy for multiple-response grinding process optimisation. Int. J. Intelligent Systems Technol. Appl., 4(1/2): 97-122.
Noorossana R, Tajbakhsh SD, Saghaei A (2008). An artificial neural network approach to multiple-response optimization. Int. J. Adv. Manuf. Technol., 40(11-12): 1227-1238.
Pasandideh SHR, Niaki STA (2006). Multi-response simulation optimization using genetic algorithm within desirability function framework. Appl. Math. Comput., 175: 366–382.
Rajakumar S, Muralidharan C, Balasubramanian V (2011). Predicting tensile strength, hardness and corrosion rate of friction stir welded AA6061-T6 aluminium alloy joints. Mater. Des., 32: 2878–2890.
Tian L, Noore A (2005). Evolutionary neural network modeling for software cumulative failure time prediction. Reliab. Eng. Syst. Saf., 87: 45-51.
Yao AWL, Liao HT, Liu CY (2008). A Taguchi and Neural Network Based Electric Load Demand Forecaster. Open Autom. Control Syst. J., 1: 7-13.