# Improvement of Committee Machine Performance to Solve Multiple Response Optimization Problems

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***Abstract*-- Three phases are considered for multiple response optimization (MRO) problems. They are design of experiments, modeling and optimization. Committee machines (CM) as a set of some experts such as some artificial neural networks (ANNs) can be applied for modeling phase. Then, genetic algorithm (GA) determines the final solution with object maximizing the global desirability as optimization phase. That algorithm was implemented on five MRO case studies include target, minimizing and maximizing objects. Current article is a development of recent authors' work on application of CM in MRO problem solving. Initial approach in that work, includes a committee machine with four different ANNs. The CM weights are specified with GA which its fitness function was minimizing the overall RMSE for each response. In current work, a new approach was applies in finding the committee machine weights. The fitness function in this approach is made by minimizing the absolute error between CM responses and real data for each response, separately. A performance index is defined to evaluate different models performance. The results from five case studies show that there are noticeable decreasing in overall RMSE whereas there is a negligible decreasing in GD for new CM with respect to initial CM. this is due that less error is a confirmation of performance increasing for new committee machine.**

***Index Term*-- Global desirability, Committee Machine, Multiple responses optimization, Genetic Algorithm**

## I. INTRODUCTION

Current study is a development in authors recent works [1]. It bodes application of committee machine in modeling of Multiple Response Optimization (MRO) problems. MRO would like to find a set of input variable amounts (x's) which yields a desired set of outputs (y's). MRO as usual is solved in three phases include experiments design, modeling and optimization.

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 [2, 3]. Also, Taguchi orthogonal arrays [4-7] 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 [2, 8, 9] 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 [10, 11]. Cheng et al. [12] used MANFIS (Multi Adaptive Neuro Fuzzy Inference System) for modeling and showed the results are superior to RSM polynomial models.

Last phase is optimization that usually is done on global desirability function. In this process, every predicted response is converted to a value between 0 to 1 by a function with name desirability function. So for all responses, a composite 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 [2], Evolutionary Algorithms such as Genetic algorithm [9, 11] and Tabu Search [10]. Also, Chatsirirungruang and Miyakawa[13] proposed a combination of GA with Taguchi and have used benefits of these techniques together to get more accurate responses.

## II. SCOPE AND LIMITATIONS

This investigation was established on five real cases from literature. There are different forms of objectives for multiple response optimization problems. They are "Target", "Minimum", "Maximum" and "In rang" objectives. As a limitation, current study and cases involve all objects except

"In rang" and this can be a good area to develop this approach in future. This article shows application of committee machine in multiple response optimization can decrease modeling errors and increase reliability of global desirability prediction. on the other hand this work introduce a container which includes different neural networks methods and also traditional modeling method or multiple regression. so due to its capacity to accept newer methods in future, capability of this approach can be increase with progress in time and method.

**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 (FF)[14], Radial Basis function networks (RBFN) [15], Generalized Regression neural network (GRNN)[16] also, Adaptive Neural Fuzzy Inference System (ANFIS) [17, 18].

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. Inputs are entered to experts, and all experts' responses are transferred to a combiner to get final response.

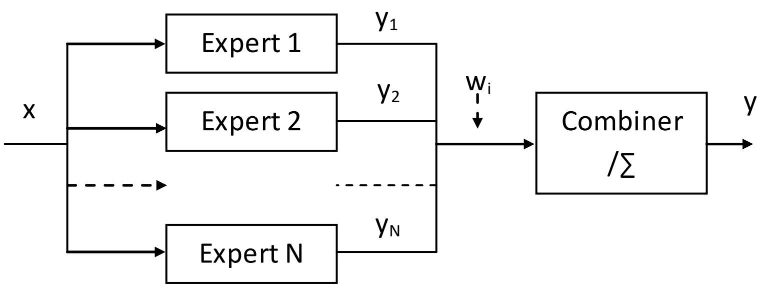


Fig. 1. A typical architecture of a committee machine based on static structure

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[19].

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

Where N is the total number of the experts used, $w_i$ is the weight coefficient of ith expert and $y_i$ is the estimated response from ith expert [20].

Genetic Algorithm could be obtained 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 [20, 21].

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

$e_i = y_{i\_ANN} - y_{i\_real}$ 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 and optimizes the fitness function. [22]; [23].

Global desirability Function is used to convert a problem of multiple responses into a single response case. By desirability function, each estimated response is converted into a dimensionless desirability value $d_i$. For different situations, $d_i$ values are defined by the continuous function which are shown in table I [24, 25].

TABLE I
DESIRABILITY FUNCTIONS FORMULA WITH DIFFERENT OBJECTS

| |
|---|
| $$d_i(y_i)=\begin{cases} 0 & y_i \leq L_i \\ \left(\frac{y_i - L_i}{T_i - L_i}\right)^s & L_i \leq y_i \leq T_i \\ \left(\frac{y_i - U_i}{T_i - U_i}\right)^t & T_i \leq yi \leq U_i \\ 0 & y_i \geq U_i \end{cases} \qquad (3)$$ The desirability for goal of "Target" |
| $$d_i(y_i)=\begin{cases} 0 & y_i \leq L_i \\ \left(\frac{y_i - L_i}{U_i - L_i}\right)^s & L_i \leq y_i \leq U_i \\ 1 & y_i \geq U_i \end{cases} \qquad (4)$$ The desirability for goal of "Maximum" |
| $$d_i(y_i)=\begin{cases} 1 & y_i \leq L_i \\ \left(\frac{U_i - y_i}{U_i - L_i}\right)^s & L_i < y_i < U_i \\ 0 & y_i \geq U_i \end{cases} \qquad (5)$$ The desirability for goal of "Minimum" |


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The parameters s and t in formulas in table 1 are convexity coefficients and specify how strictly target value will be desired. In current study, both of them are equal to one. Global desirability (GD) is defined as equation 6:

$$GD = \sqrt[N]{\prod_{j=1}^{N} d_j} \qquad (6)$$

Equations of 3 to 5, yields the desirability for different objects and equation 6 calculates the global desirability (GD). The $d_i$'s range varies from zero to one, and respectively GD rang is from 0 to 1. Important notice is that optimization of GD depends to all desirabilities and thus denoted as simultaneous optimization of all responses.

## III. METHODOLOGY

Dixit and Chandra [26] have suggested a selection method for training data sets for ANNs. They represented for n input, the minimum number of training set should be such that it includes the corners of n-dimensional space with respect to more contribution for input variables with more influence on output. But in current research, this offer was applied for corners of lower and upper limits for all variables. Training to test data numbers was 80-20 percent.

There are different criteria to assess forecasting models performance. In current work two criteria were selected to compare simulated results from models and the observed or real data. They are Root mean square error (RMSE),[27], correlation coefficient (R)[28].

$$RMSE= \sqrt{\left(\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2\right)} \qquad (7)$$

$$R=\frac{\sum_{i=1}^{N}(y_i-\bar{y}_i).(\hat{y}_i-\bar{\hat{y}}_i)}{\sqrt{\left(\sum_{i=1}^{N}(y_i-\bar{y}_i)^2.(\hat{y}_i-\bar{\hat{y}}_i)^2\right)}} \qquad (8)$$

$-1 \le R \le +1$

$\hat{y}_i$ is ith predicted value (model output), $y_i$ is the ith actual value, 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. [29]. There are two conditions to build ANNs model in the current work. The first condition is that RMSE for all data be minimum. The Second condition is that correlation coefficient of testing data is positive.

As it is mentioned, MRO solution includes three phases. First, Design of Experiments phase which in the current work, all data is selected from literatures. Second, modeling which is done by building four different neural networks include 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) [1].

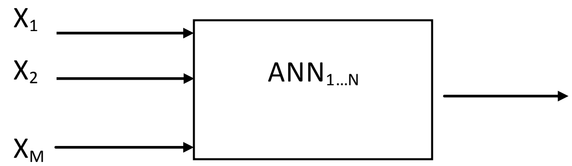



Fig. 2. Input and Outputs of every model

A committee machine (CM) was established 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 (GA) with the object to minimize absolute error between real data and CM response foe each response separately. So the total number of weights is 4 multiply by No. of ys (N) multiply by No. of experiments (r).

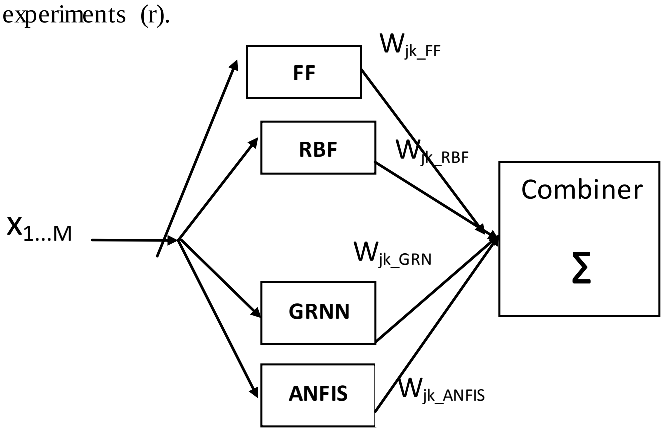



Fig. 3. Committee Machine architecture

Current article is a development of recent authors' work on application of CM in MRO problem solving. Initial approach in that work, includes a committee machine with four different ANNs. The CM weights are specified with GA which its fitness function is minimizing the overall RMSE for each response. Then, another GA determines the final solution with object maximizing the global desirability.

According to current algorithm, firstly, all ANNs are created separately to solve the MRO problem. In the modeling phase, first committee machine (CM) weights are calculated by means of GA with the object of minimizing absolute error between real responses and CM responses for each response, separately. Then as optimization phase, GA gets best responses with the object of maximizing global desirability.

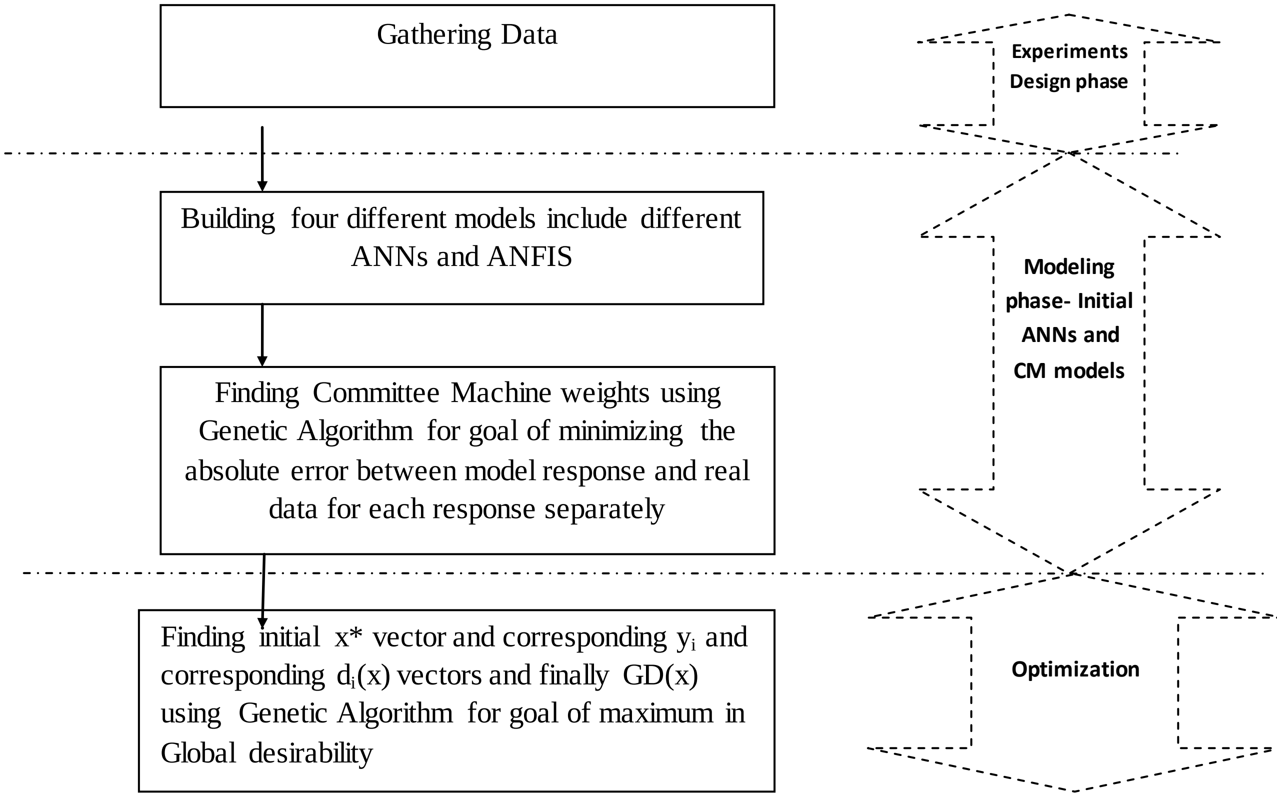



Fig. 4. Research Methodology

To evaluate performance
CMs, a model performance index (P index) is defined as formula 9. Then for all models, the P index is calculated.

$$\text{Performance Index}_{\text{model}} = \frac{GD_{\text{model}}}{\max(GD_{ANNs})} + \frac{\min(RMSE_{ANNs})}{RMSE_{\text{model}}} \qquad (9)$$

Figure 4 shows schematic of proposed methodology, also pseudocode is as follow:

```
get Data //include X,Y matrixes
setRMSE_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)
        set X and Y
if min_RMSE> RMSE_network
set min_RMSE=RMSE_network
end if
        add one to iterations
        end                           // end of while
end for

calculate CM weights using GA randomly
train network
calculate RMSE_network and coefficient of correlation
if RMSE_network<min_RMSE for goal of minimizing in overall RMSE
calculate CM weights by GA with object minimizing absolute error between y CM and y real for each response separately.
                                      // end of modeling phase
calculate X*1, y*1 and GD(X*1 )using GA for goal of maximizing in Global desirability //
```

## IV. Results and Discussion

Genetic algorithm is used for finding CM weights with object of object minimizing absolute error between y CM and y real for each response separately. Also GA was used to find final responses with maximum global desirability.
For all of them, GA specifications are as table 2.

TABLE II
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 |

Five MRO problems were selected to solve with CM. These problems contain different number of inputs and outputs, also different number of experiments. Their properties are shown in table 3.

TABLE III
CASES PROPERTIES

| Case No. | No. of x's (m) | No. of y's (N) | No. of Experiments (r) | Reference | Objects |
|---|---|---|---|---|---|
| 1 | 3 | 6 | 15 | (Noorossana et al., 2008) | T T T T T T |
| 2 | 4 | 2 | 18 | (Giordano et al., 2010) | nX |
| 3 | 3 | 3 | 30 | (Martinez Delfa et al., 2009) | T T T |
| 4 | 2 | 2 | 13 | (Bhatti et al., 2011) | Xn |
| 5 | 4 | 4 | 30 | (Aggarwala et al., 2008) | nXnn |

T:Target X:Maximum n:Minimum

**Case1:** The problem is based on the wire-bonding process in the semiconductor industry. The process inputs and outputs have shown in table 4. Different neural networks were made to model data of experiments. These ANNs specifications are listed in table 5. To have better comparison between committee machine and other neural networks, same specifications were considered for all other cases as table VI except case 3, and that was due to get acceptable results. Four ANNs include feedforward (FF), Radial Base Function (RBF), GRNN and ANFIS were consisted for every response for every problem data. So every problem has found (4*No of responses) models. Consequently, the results of other models are listed in table 6. A committee machine was made with object minimizing absolute error between y CM and y real for each response separately.

TABLE IV
INPUT AND RESPONSE VARIABLES AND OPTIMIZATION CRITERIA FOR EVERY RESPONSE (OUTPUT) IN CASE 1

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

TABLE V
NETWORKS SPECIFICATIONS FOR CASE 1

| Response | No. of neurons in hidden and output layer of feed forward | RBF Spread Coef. | GRNN Spread Coef. | 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 |

**Case2:** The problem is to optimize the yield of recombinant Oryza sativa non-symbiotic hemoglobin 1 in medium containing byproduct glycerol. The input and output variables have listed in table 7.

TABLE IV
NETWORKS SPECIFICATIONS FOR CASES 2-5 FOR ALL Y'S

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

TABLE VII
INPUT AND RESPONSE VARIABLES AND OPTIMIZATION CRITERIA FOR EVERY RESPONSE (OUTPUT) (CASE 2)

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

**Case3:** the problem is multiple response optimization of styrene–butadiene rubber (SBR) emulsion batch polymerization. The input and output variables have listed in table VIII.

TABLE VIII
INPUT AND RESPONSE VARIABLES AND OPTIMIZATION CRITERIA FOR EVERY RESPONSE (OUTPUT) (CASE 3)

| 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 |

**Case 4:** 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 variables have listed in table 9.

TABLE IX
INPUT AND RESPONSE VARIABLES AND OPTIMIZATION CRITERIA FOR EVERY RESPONSE (OUTPUT) (CASE 4)

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

**Case 5:** 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 variables have listed in table 10.

TABLE X
INPUT AND RESPONSE VARIABLES AND OPTIMIZATION CRITERIA FOR EVERY RESPONSE (OUTPUT) (CASE 5)

| Input (Independent) Variables | Output(Dependent) Variables | 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 |

Table XI represents weigths of committee machine in initial approach for case 1 and tables XII ans XIII represent these weights in new approach. As mentioned total number of weights is 36 (4*6*15).

TABLE XII
COMMITTEE MACHINES WEIGHTS BY GA IN NEW APPROACH (CASE 1_EXPERIMENTS 1-8)

| | | no_1 | no_2 | no_3 | no_4 | no_5 | no_6 | no_7 | no_8 |
|---|---|---|---|---|---|---|---|---|---|
| **FF_wights** | y1 | 0.1111 | 0.006 | 0.01 | 0.0695 | 0.3205 | 0.9886 | 0.0504 | 0.2369 |
| | y2 | 0.9995 | 0.999 | 0.2889 | 0.1605 | 0.1192 | 0.5556 | 0.1044 | 0.9908 |
| | y3 | 0.0001 | 0.9969 | 0.1605 | 0.2148 | 0.9998 | 0.3611 | 1 | 0.001 |
| | y4 | 1 | 0.0364 | 0.2577 | 0.0777 | 0.9999 | 0.3792 | 0.1111 | 0.2 |
| | y5 | 0.9962 | 0.8 | 0.1111 | 0.1671 | 0.102 | 0.0007 | 0.1583 | 0.1993 |
| | y6 | 0.1252 | 0.0067 | 0.0285 | 0.0701 | 0.0109 | 0.0383 | 0.168 | 0.9346 |
| **RBF_wights** | y1 | 0.4444 | 0.8954 | 0.286 | 0.0011 | 0.3432 | 0.0017 | 0.1522 | 0.0315 |
| | y2 | 0.0001 | 0.0006 | 0.5333 | 0.3457 | 0.4394 | 0 | 0.4273 | 0.0001 |
| | y3 | 0.7604 | 0.0018 | 0.3457 | 0.3704 | 0 | 0.4509 | 0 | 0 |
| | y4 | 0 | 0.2206 | 0.3426 | 0.7929 | 0 | 0.3104 | 0.3111 | 0.2667 |
| | y5 | 0.0006 | 0.1728 | 0.4446 | 0.4066 | 0.7505 | 0.0009 | 0.4209 | 0.5101 |
| | y6 | 0.4417 | 0.0096 | 0.1742 | 0.0313 | 0.0013 | 0.633 | 0.6069 | 0.0101 |
| **GRNN_wights** | y1 | 0 | 0.0203 | 0.0815 | 0.0595 | 0.1495 | 0.0084 | 0.6033 | 0.0236 |
| | y2 | 0.0003 | 0.0001 | 0 | 0 | 0 | 0 | 0 | 0.0017 |
| | y3 | 0.0829 | 0.0007 | 0 | 0 | 0 | 0.1686 | 0 | 0 |
| | y4 | 0 | 0.702 | 0 | 0 | 0.0001 | 0 | 0 | 0 |
| | y5 | 0.0028 | 0.0247 | 0 | 0 | 0.1323 | 0.0002 | 0 | 0 |
| | y6 | 0.2123 | 0.0359 | 0 | 0 | 0.02 | 0.0207 | 0.0276 | 0.0315 |
| **ANFIS_wights** | y1 | 0.4444 | 0.0783 | 0.6224 | 0.87 | 0.1868 | 0.0013 | 0.1941 | 0.7081 |
| | y2 | 0.0001 | 0.0003 | 0.1778 | 0.4938 | 0.4414 | 0.4444 | 0.4683 | 0.0075 |
| | y3 | 0.1567 | 0.0006 | 0.4938 | 0.4148 | 0.0002 | 0.0194 | 0 | 0.9989 |
| | y4 | 0 | 0.0411 | 0.3997 | 0.1293 | 0 | 0.3104 | 0.5778 | 0.5333 |
| | y5 | 0.0004 | 0.0026 | 0.4443 | 0.4263 | 0.0152 | 0.9982 | 0.4209 | 0.2906 |
| | y6 | 0.2209 | 0.9478 | 0.7974 | 0.8986 | 0.9678 | 0.308 | 0.1975 | 0.0239 |

TABLE XI
COMMITTEE MACHINES WEIGHTS BY GA IN INITIAL APPROACH (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 XIII
COMMITTEE MACHINES WEIGHTS BY GA IN CURRENT APPROACH (CASE 1_EXPERIMENTS 9-15)

| | | no_9 | no_10 | no_11 | no_12 | no_13 | no_14 | no_15 |
|---|---|---|---|---|---|---|---|---|
| **FF_weights** | y1 | 0 | 0.4866 | 0.032 | 0.017 | 0.0198 | 0.7359 | 0 |
| | y2 | 0.0017 | 0 | 0.9235 | 0.0306 | 0.0071 | 0.2 | 0.0002 |
| | y3 | 0.1101 | 0.993 | 0.1111 | 0.4403 | 0.1322 | 0.0215 | 0.1111 |
| | y4 | 0.1131 | 0.2 | 0.9989 | 0.52 | 0.0156 | 0.0001 | 0.9999 |
| | y5 | 0.2527 | 0.0112 | 0.9772 | 0.1605 | 0.0004 | 0.1383 | 0.0047 |
| | y6 | 0.1111 | 1 | 0.0713 | 0.0065 | 0 | 1 | 0.4269 |
| **RBF_weights** | y1 | 0.8526 | 0.333 | 0.9094 | 0.4227 | 0.9098 | 0.2205 | 0.3379 |
| | y2 | 0.7811 | 0.91 | 0.0093 | 0.2242 | 0.0355 | 0.5333 | 0.1529 |
| | y3 | 0.4447 | 0.0019 | 0.4444 | 0.0025 | 0.8094 | 0.0771 | 0.4444 |
| | y4 | 0.111 | 0.2667 | 0.0004 | 0.2391 | 0.0904 | 0.1558 | 0 |
| | y5 | 0.0557 | 0.6089 | 0.0165 | 0.3456 | 0.1245 | 0.7915 | 0.1727 |
| | y6 | 0.8889 | 0 | 0.143 | 0.0501 | 0.0744 | 0 | 0.2753 |
| **GRNN_weights** | y1 | 0.0377 | 0.1584 | 0 | 0.0452 | 0.0704 | 0.0377 | 0.6524 |
| | y2 | 0.0034 | 0.0224 | 0.0383 | 0 | 0.8781 | 0 | 0.8279 |
| | y3 | 0.0002 | 0.0042 | 0 | 0.0753 | 0 | 0.8387 | 0 |
| | y4 | 0.3388 | 0 | 0.0001 | 0 | 0 | 0.6819 | 0 |
| | y5 | 0 | 0.1671 | 0.0059 | 0.0001 | 0.735 | 0 | 0 |
| | y6 | 0 | 0 | 0.2133 | 0 | 0.1226 | 0 | 0.2631 |
| **ANFIS_weights** | y1 | 0.1098 | 0.022 | 0.0585 | 0.5151 | 0 | 0.0058 | 0.0097 |
| | y2 | 0.2138 | 0.0676 | 0.0289 | 0.7452 | 0.0792 | 0.2667 | 0.019 |
| | y3 | 0.445 | 0.0008 | 0.4444 | 0.482 | 0.0585 | 0.0628 | 0.4444 |
| | y4 | 0.4371 | 0.5333 | 0.0006 | 0.2408 | 0.894 | 0.1622 | 0 |
| | y5 | 0.6916 | 0.2128 | 0.0004 | 0.4938 | 0.1401 | 0.0702 | 0.8226 |
| | y6 | 0 | 0 | 0.5724 | 0.9434 | 0.803 | 0 | 0.0347 |

TABLE IX

COMPARISON RESULTS OF OVERALL RMSE, GD AND PERFORMANCE INDEX OF ALL MODELS (CASE1)

| Model | RMSE | Rmin/R | % change in RMSE to CM_i | GD | G/Gmax | % change in GD to CM_i | P Index |
|---|---|---|---|---|---|---|---|
| CM_new | 1.90 | 1.26 | -9.6% | 0.639 | 1.03 | 34.9% | 2.29 |
| CM_0 | 2.10 | 1.14 | 0.0% | 0.474 | 0.76 | 0.0% | 1.90 |
| ANNs Avg | 2.65 | 0.90 | 26.3% | 0.297 | 0.48 | -37.3% | 1.38 |
| FF | 2.55 | 0.94 | 21.4% | 0.566 | 0.91 | 19.6% | 1.85 |
| RBF | 2.47 | 0.97 | 17.7% | 0.000 | 0.00 | -100.0% | 0.97 |
| GRNN | 3.20 | 0.75 | 52.2% | 0.000 | 0.00 | -100.0% | 0.75 |
| ANFIS | 2.39 | 1.00 | 13.7% | 0.621 | 1.00 | 31.1% | 2.00 |

The case 1 is a famous problem in the literature and several researchers investigated different solutions. The premier author of this case was Del Castillo et al. [2]. His approach got the global desirability of 0.306. Another researcher was Ortiz et al. [11]. According to His solution methodology for this problem, the global desirability was 0.408. the third researcher was Nooroassana et al. [11]. He solved this problem with neural network approach. His methodology got GD=0.417. Finally He et al. [30]as last researcher presented GAPS method. It is a hybrid algorithm include coupling of the genetic algorithm (GA) with the pattern search (PS). According to it, the global desirability is equal to 0.363. Table 15 is a comparison of different method to solve problem case 1 and due to the lack of RMSE or MSE for all solutions, just the global desirability is compared. Remark that, current approach tends to show effect of CM with respect to its experts according to table XIV ns superior comparision will happen when both RMSE and GD be available.

TABLE XV

COMPARISON OF DIFFERENT SOLUTIONS FOR CASE 1

| Approach | GD |
|---|---|
| Del Castillo et al.[2] | 0.306 |
| Ortiz et al.[11] | 0.408 |
| Noorossana et al.[11] | 0.417 |
| HE et al.[30] | 0.363 |
| Golestaneh et al. [1] | 0.474 |
| Current approach | 0.639 |

For abstract, the weights for other cases have not showed. The results of overall RMSE and global desirability for each case are listed in tables 16 to 19. In these tables minimum overall RMSE and maximum GD are derived from best ANNs. So there is a comparison between any model include ANNs or CMs with best expert

Furthermore, another comparison in these tables are between all models and initial committee machines with respect of change percent in overall RMSE and GD.

It can be seen in all cases overall RMSE decreases and as usual GD has decreasing too. But decreasing percent of RMSE is many more than GD.

As a consequence, It can be seen that all new CMs have superior performance index than all ANNs and initial CM.

TABLE XVI

COMPARISON RESULTS OF OVERALL RMSE, GD AND PERFORMANCE INDEX OF ALL MODELS (CASE2)

| Model | RMSE | Rmin/R | % change in RMSE to CM_i | GD | G/Gmax | % change in GD to CM_i | P Index |
|---|---|---|---|---|---|---|---|
| CM_new | 0.07 | 6.72 | -76.1% | 0.720 | 0.77 | -1.1% | 7.49 |
| CM_0 | 0.29 | 1.61 | 0.0% | 0.727 | 0.78 | 0.0% | 2.39 |
| ANNs Avg | 0.54 | 0.86 | 86.1% | 0.747 | 0.80 | 2.7% | 1.66 |
| FF | 0.67 | 0.70 | 128.2% | 0.933 | 1.00 | 28.3% | 1.70 |
| RBF | 0.47 | 1.00 | 60.7% | 0.694 | 0.74 | -4.5% | 1.74 |
| GRNN | 0.56 | 0.85 | 89.9% | 0.586 | 0.63 | -19.4% | 1.47 |
| ANFIS | 0.48 | 0.97 | 65.7% | 0.774 | 0.83 | 6.5% | 1.80 |

TABLE XVII
COMPARISON RESULTS OF OVERALL RMSE, GD AND PERFORMANCE INDEX OF ALL MODELS (CASE3)

| Model | RMSE | Rmin/R | % change in RMSE to CM_i | GD | G/Gmax | % change in GD to CM_i | P Index |
|---|---|---|---|---|---|---|---|
| **CM_new** | 0.98 | 5.62 | -74.2% | 0.969 | 0.97 | -1.6% | 6.60 |
| **CM_0** | 3.81 | 1.45 | 0.0% | 0.985 | 0.99 | 0.0% | 2.44 |
| **ANNs Avg** | 9.53 | 0.58 | 150.2% | 0.978 | 0.98 | -0.7% | 1.56 |
| **FF** | 10.54 | 0.53 | 176.7% | 0.985 | 0.99 | 0.1% | 1.51 |
| **RBF** | 5.54 | 1.00 | 45.3% | 0.998 | 1.00 | 1.3% | 2.00 |
| **GRNN** | 14.70 | 0.38 | 285.9% | 0.933 | 0.93 | -5.3% | 1.31 |
| **ANFIS** | 7.34 | 0.75 | 92.8% | 0.995 | 1.00 | 1.1% | 1.75 |

TABLE XVIII
COMPARISON RESULTS OF OVERALL RMSE, GD AND PERFORMANCE INDEX OF ALL MODELS (CASE4)

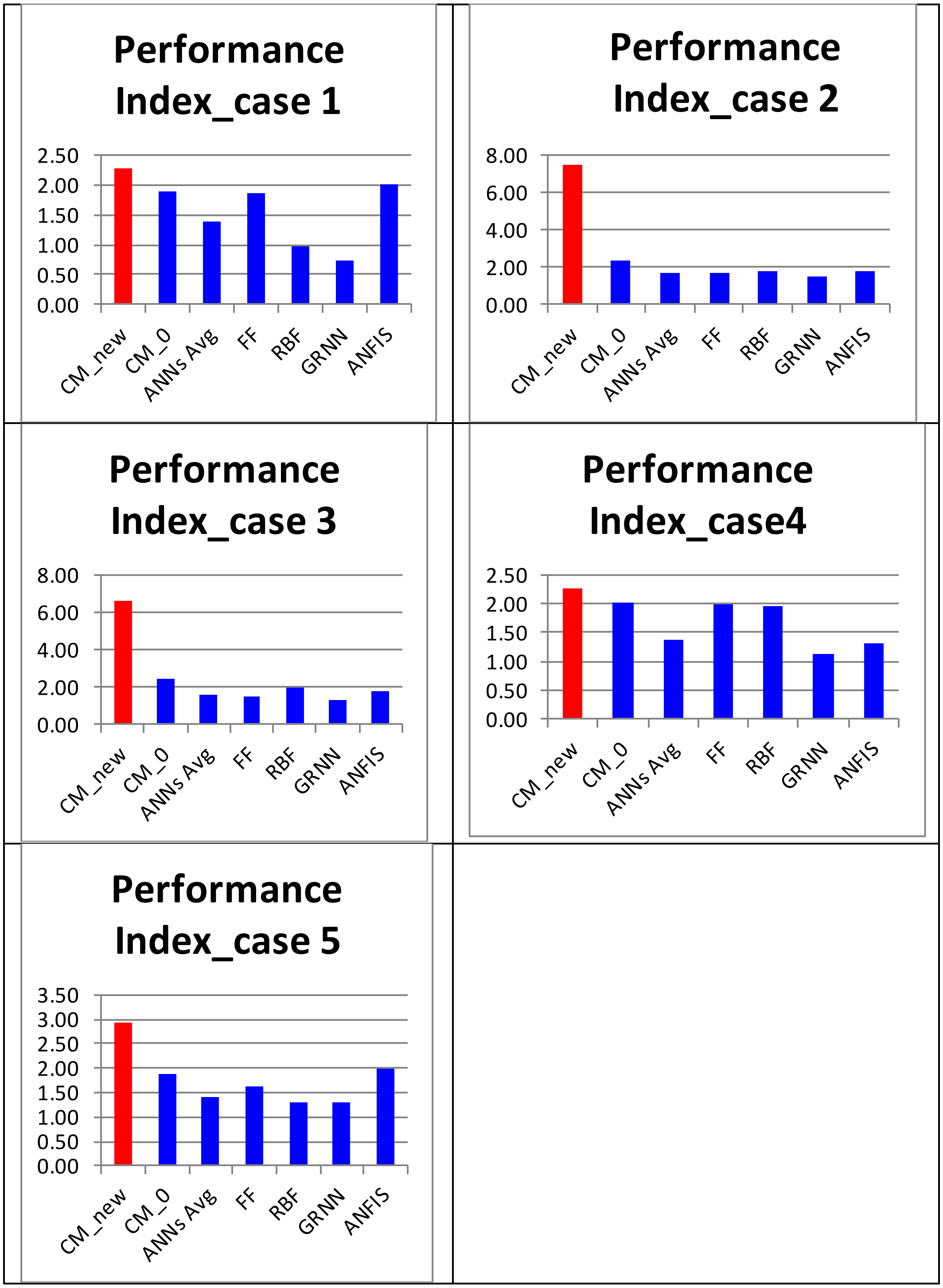
| Model | RMSE | Rmin/R | % change in RMSE to CM_i | GD | G/Gmax | % change in GD to CM_i | P Index |
|---|---|---|---|---|---|---|---|
| **CM_new** | 0.35 | 1.30 | -22.2% | 0.854 | 0.97 | -4.2% | 2.28 |
| **CM_0** | 0.45 | 1.01 | 0.0% | 0.891 | 1.02 | 0.0% | 2.03 |
| **ANNs Avg** | 1.16 | 0.39 | 158.8% | 0.854 | 0.98 | -4.1% | 1.37 |
| **FF** | 0.46 | 0.99 | 2.2% | 0.876 | 1.00 | -1.8% | 1.99 |
| **RBF** | 0.45 | 1.00 | 1.5% | 0.853 | 0.97 | -4.3% | 1.97 |
| **GRNN** | 2.38 | 0.19 | 431.6% | 0.828 | 0.95 | -7.1% | 1.14 |
| **ANFIS** | 1.34 | 0.34 | 199.8% | 0.861 | 0.98 | -3.4% | 1.32 |

TABLE XIX
COMPARISON RESULTS OF OVERALL RMSE, GD AND PERFORMANCE INDEX OF ALL MODELS (CASE5)

| Model | RMSE | Rmin/R | % change in RMSE to CM_i | GD | G/Gmax | % change in GD to CM_i | P Index |
|---|---|---|---|---|---|---|---|
| **CM_new** | 2.00 | 1.97 | -54.3% | 0.892 | 0.98 | -1.3% | 2.95 |
| **CM_0** | 4.38 | 0.90 | 0.0% | 0.904 | 1.00 | 0.0% | 1.89 |
| **ANNs Avg** | 9.23 | 0.43 | 110.9% | 0.905 | 1.00 | 0.1% | 1.42 |
| **FF** | 6.19 | 0.63 | 41.6% | 0.908 | 1.00 | 0.5% | 1.63 |
| **RBF** | 13.26 | 0.30 | 203.1% | 0.904 | 1.00 | 0.1% | 1.29 |
| **GRNN** | 13.53 | 0.29 | 209.1% | 0.901 | 0.99 | -0.3% | 1.28 |
| **ANFIS** | 3.93 | 1.00 | -10.2% | 0.907 | 1.00 | 0.4% | 2.00 |

The graphical result for better comparison is presented in table 20.

TABLE XX
GRAPHICAL COMPARISON OF DIFFERENT MODELS PERFORMANCE FOR ALL FIVE CASES

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## CONCLUSION

Different artificial neural networks (ANNs) are used for modeling of multiple response optimization (MRO) problems. Committee machine is a collection of several elements or experts such as ANNs. Current study is a development of recent authors work on application of committee machine to solve MRO problem. In current new approach, all weights of CM are calculated by genetic algorithm that its fitness function is minimizing absolute error between CM response and real data for each respons. This new approach yields noticeable decreasing in overall RMSE of new CM with respect to initial CM. also there is a negligible decreasing in global desirability. But due to higher accuracy of new CM, its performance is superior than previous one. The results of five case studies include target, minimizing and maximizing objects, represent the improvement in committee machine performance with new approach. Current study represents a classic approach of CM to solve MRO furthermore new approach, which causes development in performance of modeling. In this study, all experts was utilized together, and as a future work it can be investigate the priority for each expert. In addition, combination of experts is a good subject to develop this approach. Another area to development of current work is investigation about possibility of overfitting in modeling by committee machines.

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