IMPLEMENTATION OF DUAL RESPONSE APPROACH TO CONCRETE MIX DESIGN BASED ON HYBRID NEURAL NETWORK-GENETIC ALGORITHMS
(PRELIMINARY STUDY)

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ABSTRACT

Process parameters prediction in robust design is very important. If the predictions results are fairly accurate thenthe quality improvementprocess will save time and reduce cost. The concept of dual response approach based on response surface methodology has widely investigated. Separately estimating mean and variance responses, dual response approach may take advantages of optimization modeling for finding optimum setting of input factors.A sufficient number of experimentations are required to improve the precision of estimations. Research on optimization of concrete mix design to achieve adequate strength is of considerable importance. In a concrete mix design, as the number of mix variables increases the number of experiments also increases. This study proposed an alternative dual response approach without performing experiments. Neural Network – Genetic Algorithmscan be appliedto model relationships between responses and input factors. Using empirical process data, process parameter can be predicted without performing real experimentations. This is a wise solution to minimize the environmental impacts due to using of raw material wasted.An optimization of brick with concrete mix design has been investigated to demonstrate the procedures and applicability of the proposed approach.

Keywords: dual response approach, algorithms

1. Introduction

RPD is a method to determine the optimal conditions of input variables to give the optimal response. Taguchi used of orthogonal array and SN ratio on the inner array to factors beyond the control and outer factors for noise factor, then the combination of the best design parameters are determined by minimizing the SN ratio (Taguchi, 1987). Koksoy and Yalcinoz (2005) proposed a Hopfield neural network approach to solve dual response systems problems. They found that this approach is capable for minimizing multi-objective functions.Arungpadang and Kim Young Jin (2012) have constructed and validated BPNN models based on happenstance data. This research applied RSM to estimate mean and variance responses for the purpose of RPD.

Some limitation can be found in the training step of the BPNN. The BPNN often gets trapped in a local minimum because the use of gradient descent (Ma and Su, 2010). Research combining NN and GA began to appear around 1988s. The primary direction of using the GA is to improve the performance of NNs through finding optimal NN architecture or parameter setting as an alternative of BPNN to optimize the network (Sexton et.al., 2004).

The combination of NN and GA has been used for integrated process modeling and optimization. The hybrid NN-GA technique is a powerful method for process modeling and optimization that is better than other techniques such as response surface methodology, particularly for complex process models.

Now, fly ash is using extensively for utilization of industrial wastes by producing cost-effective and durable building components. This material is a by-product of the coal combustion in thermal power generation and consists mainly of Fe_2O_3, SiO_2, CaO, Al_2O_3, and some impurities. The use of mineral admixtures has a positive effect on the quality of concrete by binding the $Ca(OH)_2$.Chauliaand Das (2008)have been used fly ash, coarse sand, and stone dust as mineral admixtures for making bricks. Using low calcium content of the fly, its behavior is like a pozzolanic admixture in the brick. The addition of fly ash can also increase workability due to its spherical shape and their extreme fineness at lower contents.

Compressive strength is a vital parameter to judge the durability/stability of the brick. Hence, studies on optimization of brick with concrete mix design to achieve adequate strength is of considerable importance. In a concrete mix design, as the number of mix variables increases the number of experiments also increases. The traditional approach for such experimental studies is to use full factorial or fractional factorial design followed by response surface modeling. However, in the case of a full factorial design the number of experiments is numerous, and it is practically not possible to carry out the experiments in majority of situations.

Precisely, parameter design technique leads to achieve high quality of a product or component at low cost. Thus the objective of the present study is to find out the optimum mix design for making brick so as to achieve the maximum compressive strength.

2. Hybrid BPNN-GA Procedure

The DRA based hybrid NN-GA using in this study consists of three stages, firstly, happenstance (or experimental) data are collected to construct a BPNN to represent the input-response relationship, based on the predicted mean and standard deviation responses, for a given setting of input factors within the feasible solution space. Secondly, the population initialization is conducted. Afterwards, the fitness computation and scaling are carried out. Then GA's procedures are applied. Finally, the optimum parameter set are obtained based on the mean and standard deviation response. The overall procedure of the proposed approach is described in figure 1.

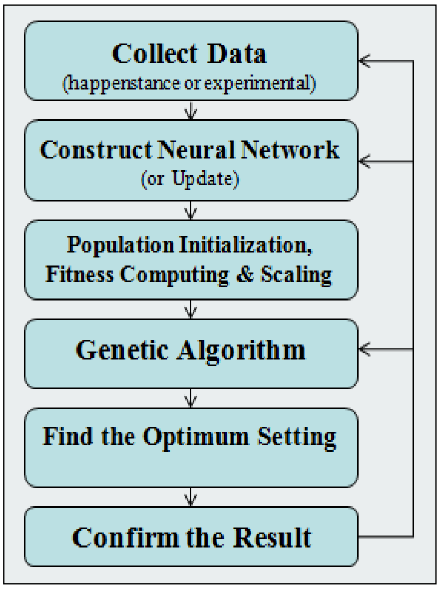

Figure 1. Hybrid BPNN-GA approach

(1) Construct and Training BPNN
Determine experimental data used for training and testing the BPNN model. Establish the network architecture (input, hidden, and output layers). Search the optimal network architecture and confirm that the network is not overfitted. Convert the experimental input and output data to number within the range [-1, 1]. The normalization is performed in order to avoid mismatch between the influence of some input values and the network weights and biases. Then, train the network using the normalized data by utilizing a training function of Levenberg-Marquardt.

(2) Population Initializing, Fitness Computation and Scaling
Adjust the initial generation index to zero, the populatian number and the number of independent variables. Generate a random initial population. Every individual has vector entries with certain lengths which are divided into many segments. Next, the performance of the solution vector in the current population is computed by using a fitness function. Convert the solution vector to number between -1 and 1. Then, the vector is entered as an input vector to the training process to obtain the corresponding outputs. After that, scale the raw fitness scores to values in a range that is appropriate for the selection function. In the GA, the selection function applies the scaled fitness values to pick the parents for the next generation. The performance of the GA is affected by the range of the scaled values. The scaling function employed in this algorithm is based on the rank of each individual by its score. Lower raw scores have higher scaled values since the algorithm minimizes the fitness function.

(3) Genetic Algorithms Procedures
Select the parents based on their scaled values by taking the selection function. The selection function specifies a higher probability of selection to individuals with higher scaled values. Each individual can be chosen more than once as a parent.

Options of reproduction specify how the GA produces children for the next generation from the parents. Elite count specifies the number of individuals with the best fitness values that are assured to withstand to the next generation. Arrange elite count to be a positive integer within the range (elite children). Cross over fraction decides the fraction of each population that are produced by crossover. The rest of individuals in the next generation are produced by mutation. Set crossover fraction to be a fraction between 0 and 1. Cross over allows the algorithm to extract the best genes from different individuals. That process occurs by choosing genes from a pair of individuals in the current generation and recombining them. The output is potentially superior children for the next generation. The probability is equal to crossover fraction. Mutation function performs small random changes. It gives genetic diversity and therewith increases the possibility to create individuals with better fitness values.

The recent population is replaced with the children to form the next generation since the reproduction is made. Next process is the increment of the generation index (Gen = Gen + 1). Then, repeat the fitness computation stage to increment of generation stage, until convergence is achieved. The algorithm stops if one of the following five conditions is met. They are fixed generations, fitness limit, times limit, stall generations or stall time limit. If the convergence criterion is achieved, the children with the highest ranking based on the fitness value are decided to be the optimal parameter set of the population.

3. Data and Analysis

A 3^3 factorial experiment is now designed within the range of interest to estimate the response functions of process mean and SEM by applying RSM. A feed-forward BPNN is used to construct PDE and SD estimation. Mean and SD responses at each design point are obtained by using the model architecture. A neural network and global optimization toolbox in Matlab R2012b is used to construct the hybrid BPNN-GA model. The network consists of four inputs, two hidden layers, and two outputs. The coded values of the input factors are shown in Table 1 and 2.

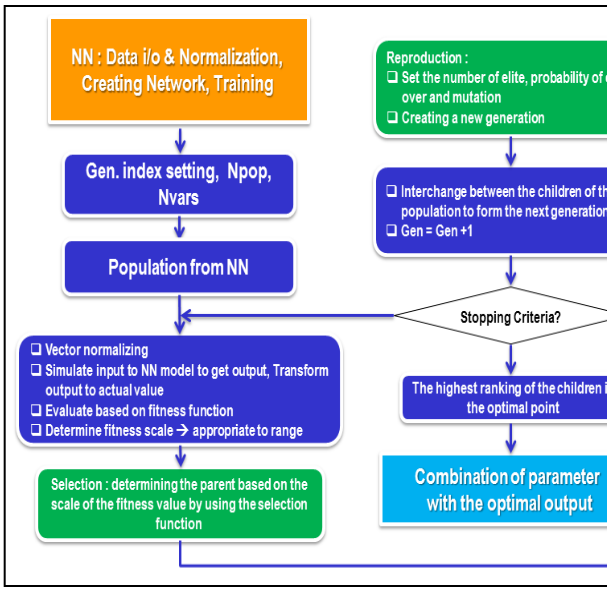

Figure 2 Matlab's flowchart of BPNN-GA

BPNN-GA approach procedure (fig. 1) can be implemented using Matlab R2014a as described in figure 2. Considering the procedure outlined in this figure, the first step is to define the input and output data and normalize them (before network creating and training process of neural network). Then, generation index, number of population and number of variables are specified. GA is undertaken to select subsets of solutions from NN's population, called parents, and combine them to produce new solutions called children. This selection process can be done after the population is evaluated and sorted based on its fitness function. After that, rules of combination to yield children are applied based on the genetic notion of crossover together with elitist selection and occasional operations such as random value changes (mutations). These children will undertake a survivability test. If the children pass the survivability test, they can be chosen as parents for the next generation. The selection and reproduction process is repeated until one of the stopping criteria is met.

Global Optimization Toolbox of Matlab 2012b provides methods to search for global solutions for problems that contain multiple maxima or minima, which includes the GA solvers. This solver supports algorithmic customization. A custom GA variant can be created by modifying initial population and fitness scaling options or by defining parent selection, crossover, and mutation functions.

In the next step, hybrid BPNN-GA model is simulated to obtain the optimal parameter within the feasible solution space of the system. The values of the three control factors are set as continous and fall in the range between -1 (lower bound value) and 1 (upper bound value). The operational conditions of GA are set as: population size, cross over fraction, number of generation, fitness scaling function, selection function, crossover function, mutation function and mutation probability. The display of coding in m-file and the running result windows from hybrid BPNN-GA model can be seen in figure 3.

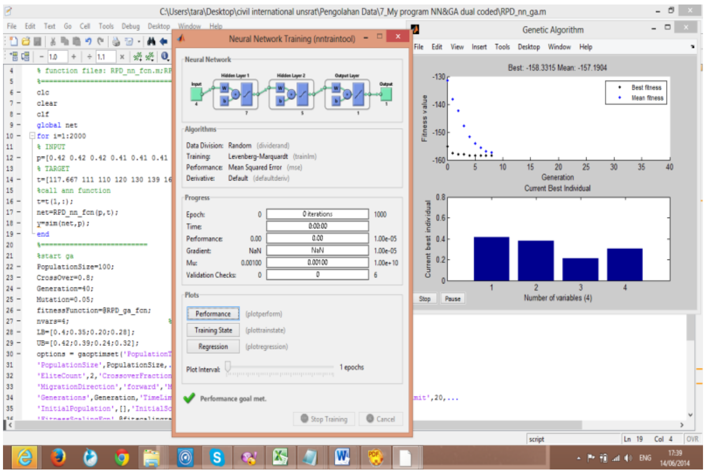

Figure 3. Matlab's m-file and result

Table 1 and 2 shows the estimated value of response's mean. Each of the estimated values has its own optimal combination of parameter A, B, C and D.This table shows us that by applying certain combination of parameters settings, mean value between 110 ± 5 to 162 ± 1.73 can be obtained.

Table 1. Predicted mean and standard deviation responses using real value

	A	B	C	D	R1	R2	R3	Mean	SD
1	0.42	0.35	0.24	0.28	113	117	123	117.67	5.03
2	0.42	0.37	0.22	0.3	113	100	120	111	10.15
3	0.42	0.39	0.2	0.32	113	110	107	110	3
4	0.41	0.35	0.22	0.32	123	117	120	120	3
5	0.41	0.37	0.2	0.28	117	133	140	130	11.79
6	0.41	0.39	0.24	0.3	133	147	137	139	7.21
7	0.4	0.35	0.2	0.3	163	163	160	162	1.73
8	0.4	0.37	0.24	0.32	143	147	153	147.67	5.03
9	0.4	0.39	0.22	0.28	163	160	160	161	1.73

Table 2. Predicted mean and standard deviation responses using coded value

	A	B	C	D	R1	R2	R3	Mean	SD
1	1	-1	1	-1	113	117	123	117.67	5.03
2	1	0	0	0	113	100	120	111	10.15
3	1	1	-1	1	113	110	107	110	3
4	0	-1	0	1	123	117	120	120	3
5	0	0	-1	-1	117	133	140	130	11.79
6	0	1	1	0	133	147	137	139	7.21
7	-1	-1	-1	0	163	163	160	162	1.73
8	-1	0	1	1	143	147	153	147.67	5.03
9	-1	1	0	-1	163	160	160	161	1.73

4. Discussion

Referring to the analysis, hybrid BPNN-GA model can predict quite well the mean and SD value. Its value is similar to the result of Chaulia and Das (2008). The result needs to be validated by conducting a confirmation experiment to see if the desired responses are obtained. The most important thing is hybrid BPNN-GA model gives an alternative method to solve and predict the optimal parameters despite limited number of experimental runs, which allows decision making to be taken quickly, reduces the total cost and shorten the process time.

5. Conclusions

Optimization of process parameters for fly ash brick was performed via hybrid BPNN-GA model. An L9 OA was used to accommodate four control factors and each with three levels for the experimental plan. Selected process parameters along with their levels were: water /binder ratio (0.42, 0.41, 0.40); fly ash (35, 37, 39%); coarse sand (24, 22, 20%); stone dust (28, 30, 32%). An optimized value of the compressive strength for a 95% confidence interval was predicted as (166.22 ± 10.97) kg.cm^{-2}. From confirmation experiments, the mean value of the compressive strength corresponding to the optimum conditions was obtained as 160.17 kg.cm^{-2}, which fell within the predicted range. Thus the predictions made by BPNN-GA model were in good agreement with the confirmation results.

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