Optimization of genetic algorithm parameter in hybrid genetic algorithm-neural network modelling: Application to spray drying of coconut milk

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Abstract. Application of Artificial Neural Network (ANN) and Genetic Algorithm (GA) are to provide an accurate model of the spray drying system. In this study, a comparative study is performed between ANN and GA enhanced ANN to estimate their abilities in emulating the spray drying process of coconut milk powder under restricted parameters. The GA parameter is optimized through response surface methodology (RSM). Through RSM, GA parameter such as population size, mutation and crossover are optimized and is used for the development of GA-ANN network. The optimized GA parameters values are at maximum population size (100), minimum crossover rate (0.2) and maximum mutation rate (1.0). The optimized GA parameters is then applied in the development of the GA-ANN network as the networks applied genetic algorithm to determine the initial weights in its neural network. Both models are then compared by placing importance of highest correlation of determination ($R^2$) and lowest mean square error (MSE) values. The results have shown GA-ANN’s MSE (0.033396) is lower than ANN’s MSE value (0.082263), which the GA-ANN’s $R^2$ value (0.88245) is higher than ANN (0.8499). This have shown that GA as a global search technique can be integrated in the development of the ANN.

1. Introduction

Spray drying is a well-established unit operation application for converting liquid feed material into powder form. The spray drying potential lies in its continuous operation, wide range of operating temperatures, short residence times, flexibility in capacity design and suitability of multiple heat sensitive and resistant materials. However, developing an accurate mathematical model of the spray drying process is a complicated procedure. It involved application of multiple engineering knowledges such as heat and mass transfer to describe the relationship between the processing conditions and the powder properties [1]. Artificial neural network (ANN) has been proposed as a simpler alternative modelling technique for spray drying process. Accurate modelling and control of food processing operations (such as spray drying) require high precision and responses, in which neural networks can be implemented into a simulation without understanding the theoretical background of the study [2]. Furthermore, ANN does not heavily rely on intensive knowledge, assumptions and the nature of spray drying mechanisms, as to map out the nonlinearity structures between the operating parameters and powder properties [3].
As one of the main criteria in neural network development, weight optimization is critical especially in the training phase of the neural network development. This phase often focused on each weights of the neural connection to be determined and establishing a network with parameters that can achieve accurate output [4]. Therefore, the training phase should produce an optimized weight configuration associated to the minimum output error. The concept of objective function is placed as an importance in this study, as in developing an optimized weight of a trained artificial neural network prompts huge number of variables and multiple configurations to be investigated [5]. In this case, the neural network highly relies on its learning algorithm on each neuron’s weight changes in the training phase. However, the drawback of ANNs is on their learning algorithm, the backpropagation technique. The technique’s foundation heavily relied on multiple iteration of gradient error calculation and adjusts the network’s weights and biases throughout the training phase. The shortcoming on this method is the random initial weight setting as the training phase begins. With random initial weights, training of the neural network often leads towards two different setbacks: unable to escape local minima points in the search space and slow converging in locating global minima point [6].

Genetic Algorithm (GA) is presented as a complimentary technique to overcome the limitation of the ANN. In further refine the GA purpose for this study, the technique is used to optimize weights of the ANN in the training phase. This ensure that the neural network does not relied on random initial weights but heavily relied on natural evolution algorithm to determine the best optimal weights. The potential of ANN is further enhanced using GA as evolutionary search and optimization algorithm based on natural genetic evolution and natural selection [7]. Utilization of both techniques have been used by in determining the optimal processing condition for spray drying whole milk powder to produce milk quality of maximum free fat content, maximum lactose crystallinity and minimum average particle size [8]. The neural network is used as predictor to evaluate the processing condition of the spray drying condition during genetic algorithm optimization. Multiple food science studies have emphasized on evaluation of ANN supported GA for optimization problem such as baker’s yeast fermentation [9], green tea leaves [10] and vegetable oil hydrogenation process [11]. The use of genetic algorithm served as a purpose of optimization of the lactose crystallinity and free fat content in the neural network modelling. Assigning Genetic Algorithm (GA) is a solution in overcoming the setbacks of an ANN. Furthermore, the assigned fitness function to the problem is to be well-defined to ensure that GA performed accordingly based on the objective of the study. Undefined fitness function to the problem poses wrong solution to the problem [12]. However, GA as an optimization technique has its own parameters to be concerned. Implementation of GA as an optimization technique requires tuning of GA parameters such as crossover, mutation and population size. Based on a review paper produced by various authors, most studies that utilized GA as an optimization technique often defined the GA parameters in an ad hoc fashions and lack well-designed experiments [13].

Currently, there are no studies done on optimizing GA parameters in the area of ANN-GA modelling study and spray drying coconut milk modelling. Proposed method of integrating GA into RSM has shown more efficient than the trial and error method with lower requirement of experimentations. It was proven that integration of GA coupled with RSM into ANN reduces the number of experimentations done by more than 70% with the purpose of optimizing the neural network topology using GA [14]. Utilization of GA parameter optimization such as crossover, mutation and selection function using design of experiments method, has provided deeper insights on the effect of GA parameters [15]. By experimenting different level of GA parameters and analysis of variance, results have shown to provide an optimum GA parameter in a lower completion time compared to the trial and error method. The objective of this paper is to optimize the selected GA parameters in the ANN-GA modelling of spray drying of coconut milk through RSM.

2. Materials and methods

2.1. Framework of genetic algorithm enhanced neural network
Based on Figure 1, the research framework utilized the optimization of GA parameters using RSM method which followed by the development of ANN-GA network and its comparison performance with ANN of similar architecture. A total of 20 number of combinations of independent variables: crossover (immediate crossover), mutation (Gaussian mutation) and number of population (integers) were proposed using the $2^k$ factorial design of MINITAB. The data produced from the proposed design experiments were analyzed using analysis of variance (ANOVA). Statistical significance was set at P<0.05 using MINITAB.

The selected GA parameters chosen are optimized based a minimization MSE function (cost function) of the neural network. Obtained optimized GA parameters are used in the development of ANN-GA and is further compared with ANN in terms of highest $R^2$ value and lowest mean square error (MSE) value. Both GA-ANN and standalone ANN incorporate with the architecture design of Levenberg-Marquart learning algorithm, transfer function of hyperbolic tangent sigmoid and 3-8-2-3 topology configuration.

To determine the effect of parameters on the GA performance in term of fitness value, design of experiment (DOE) is applied as the main purpose of this technique provide estimation on the input factors produced changes of responses. As a tool of DOE, factorial design is used in this study is the $2^k$ factorial design, whereas 2 represents the two level of k factors. The level set for the two level for each parameter are set the low level and high level. The selection of this method is due to the reason that strong and significant conclusion can be extracted from analyzing the opposite value [16]. Therefore, the optimal range of these parameter are based on theoretical studies that is summarized in Table 1:

![Data collection using 2\(^k\) Factorial Design based on ANN architecture](image1)

![](image2)

![Optimization of GA parameters using minimization MSE function](image3)

![Development of GA-ANN using optimized parameter](image4)

![Comparison of GA-ANN with ANN based on $R^2$ and MSE values](image5)

**Figure 1.** Research Framework.

**Table 1.** Factors and levels for factorial design.

| Parameter          | Low Level | High Level |
|--------------------|-----------|------------|
| Crossover          | 0.2       | 1.0        |
| (Intermediate Crossover) |          |            |
| Mutation           | 0.2       | 1.0        |
| (Gaussian Mutation) |          |            |
| Number of Population | 20       | 100        |
Based on Table 1, there are three parameters considered in the factorial design, which are the crossover, mutation and the number of populations. The type of crossover used is the intermediate crossover that has a low level of 0.2 and high level of 1.0 (maximum value). The type of mutation used is the Gaussian mutation which has a low level of 0.2 and high level of 1.0 (maximum value). For the number of populations, there are no limit to number of populations, however the low level of 20 and the high level of 100 (in the form of integers) are restricted as the range is realistic for $2^k$ factorial design to interpret and analyze a linear relationship [17].

2.2. GA algorithm development

Based on the research framework, the training and test dataset is inserted into GA MATLAB code. At first, random generated weights are selected as group of individuals (population) and is tested against the objective function of the developed neural network. The selected population proposed by the GA code is further evolved through crossover and mutation operators with a point of purpose to achieve the objective function assigned. The MATLAB default mutation and crossover operator which are intermediate crossover and Gaussian mutation were used in this study [18]. Repetition of crossover and mutation produced generation of populations to achieve the objective function. The process stopped as the objective function or the stopping criterion assigned has achieved. As a result of the GA algorithm, the initial weights are obtained and then assigned for the ANN network.

2.3. Cost function

The cost function evaluates the design and requirement of neural network based on the variables that is assigned for the study purpose, using the 3-8-2-3 neural network topology configuration. The final objective of achieving optimization in neural network weights and mean square error (MSE) is based on a cost function [6] and is defined generally as:

$$C(w, b) = \frac{1}{2n} \sum_{i=1}^{n} \|y(x) - a\|^2$$

where $w$ denotes all the weights in the network (46 weights), $b$ as the all the biases (10 biases), $n$ is the total number of training inputs, $a$ is the vector of outputs from the network when $x$ is the input and $y(x)$ is the sum of inputs of $x$.

2.4. Comparison performance of ANN and GA-ANN models

The assigned initial weights for ANN network, the input training sample for training and learning is inserted for the development of ANN. Throughout the training process, the initial weights are continuous updated based on the comparison of the MSE values. The training process stopped when the MSE values has achieved the targeted stopping criterion which was set at $1 \times 10^{-3}$. The evaluation of the network prediction performance in comparison to real experiment data is based few criterions, which are correlation of determination, $R^2$ value and mean square error (MSE) is used for this study.

The formula for the criterions is given as followed:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (\bar{T}_{p,exp,i} - \bar{T}_{p,cal,i})^2$$

$$R^2 = \frac{\sum_{i=1}^{N} (T_{p,exp,i} - \bar{T}_{p,exp,i})^2 - \sum_{i=1}^{N} (T_{p,exp,i} - \bar{T}_{p,cal,i})^2}{\sum_{i=1}^{N} (T_{p,exp,i} - \bar{T}_{p,exp,i})^2}$$

where $T_{p,exp,i}$ and $T_{p,cal,i}$ are the average number of experiments and calculated spray drying for its observation and $N$ is the number of runs. The singularity concept for the model is achieve the smallest MSE with largest $R^2$ as possible [19]. The MSE and $R^2$ of ANN-GA model is compared with another separate ANN model that has the same neural network design of Levenberg-Marquart learning
algorithm, transfer function of hyperbolic tangent sigmoid and 3-8-2-3 topology configuration, with the entire datasets divided into 70\% (training dataset), 15\% (validation dataset) and lastly 15\% (testing dataset) for the process of ANN development.

3. Results and discussion

3.1. GA parameter tuning using RSM - $2^3$ factorial design

The neural network for the spray drying of coconut milk is further enhanced through GA parameters optimization. Optimization of the GA algorithm, which consists of parameters that have significant impact on the neural network performance, leading towards the importance of GA parameter tuning. Each factor of the GA is further optimized using RSM method using the three parameters (population size, crossover rate and mutation rate) against the best fitness value recorded. Based on Table 2, the average of the best fitness value from 5 separate reading were obtained based $2^3$ factorial experimental design, that is further illustrated in Figure 2. Average reading taken to ensure results consistency and fair representation of the data.

The results of Table 2 have shown that the best performing factor has the lowest fitness value of 0.070340, which consists maximum population of 100, crossover rate of 0.2 and highest mutation rate of 1.0. On the other hand, the highest fitness value of 0.224280 applied the parameter value: population size of 20, crossover rate of 0.2 and mutation rate of 0.2. The effect of each factor is further emphasized in the next section using statistical technique of MINITAB.

The three factors which are population size, crossover and mutation rate were considered in determining the best GA tuning for the GA parameters optimization. Both crossover and mutation operators have an effect on the evolution of population over time and the consideration factor have to be taken on number of generations as the probability of producing the best optimal value is highly to be found [20]. Furthermore, population size is an important criterion on the performance of GA as its cross-influences with other parameters. As the GA mechanism progresses at each generation, larger population size does not evolve and become homogenous quickly, unlike its smaller counterpart [21]. In a study done for the development of nutritional guidance application, three GA parameters were taken into considerations in an algorithm that incorporate personal health data, nutritional values of food taken and meal diary to create a nutritional guidance [22].

![Figure 2. $2^3$ Cube Plot Design with fitted means.](image-url)
Table 2. Factorial design result based on $2^3$ level design.

| Population Size | Crossover | Mutation | Average Reading |
|-----------------|-----------|----------|-----------------|
| 100             | 1         | 1        | 0.070430        |
| 20              | 0.2       | 1        | 0.218220        |
| 20              | 1         | 1        | 0.070386        |
| 20              | 1         | 0.2      | 0.073200        |
| 100             | 0.2       | 1        | 0.070362        |
| 100             | 1         | 0.2      | 0.071402        |
| 100             | 0.2       | 0.2      | 0.221400        |
| 20              | 0.2       | 0.2      | 0.224280        |

3.2. Validity of the GA parameters
The validation of the GA parameters is then checked using different statistical method. The first statistical method ANOVA is used to determine the significance of each parameter. ANOVA table is obtained by using the statistical software package Minitab Version 17. The last column indicates the significance of effect and the previous column indicates the F-statistic used for the significance test which is summarized in Table 3. The F-test is further defined as the ratio between groups means square values within group square values and the P values are used to investigate the significance of each coefficient. Therefore, if the P values is less than 0.05, the value itself represent a high significance of corresponding coefficient.

Table 3 have shown that the all three parameters; population size, crossover and mutation have achieved significant in parameter values as all three parameters recorded lower than 0.05. However, crossover parameter (0.04) barely achieved significant of coefficient. In other word, crossover has lower capability in generating newer generations that does not lead to low fitness value which is the objective function of the algorithm. In the area of food processing, GA parameter tuning has a critical impact on process modelling cultivation of S. cerevisiae through fermentation. The study revolves on investigation on multiple genetic algorithm parameters, namely, selection, crossover and mutation on the model performance [23]. The fermentation process is complex, time varying and is highly non-linear, leading towards the use of GA algorithm as a global stochastic optimization in process modelling. Similar parameters were used to generate individuals in solving an assembly line problem, in which the crossover population did not achieve significance value in comparison to other parameters [24]. In the same study, both mutation and population size parameters have positive significance effect on the fitness function. The authors have emphasized that increasing the population size enlarges the search space, leading towards high possibility of achieving better solution and mutation ensured that diversity of individuals produced variations of better generations.

Table 3. ANOVA results for fitness response.

| Factor         | Type   | Level | Values  |
|----------------|--------|-------|---------|
| Population Size| Fixed  | 2     | 20, 100 |
| Crossover      | Fixed  | 2     | 0.2, 1.0|
| Mutation       | Fixed  | 2     | 0.2, 1.0|

Analysis of Variance for Fitness Value

| Source       | DF | SS        | MS     | F   | P    |
|--------------|----|-----------|--------|-----|------|
| Population Size| 1  | 0.002621  | 0.002621| 0.90| 0.0031|
| Crossover    | 1  | 0.026282  | 0.026282| 9.03| 0.040|
| Mutation     | 1  | 0.003329  | 0.003329| 1.14| 0.034|
| Error        | 4  | 0.011636  | 0.002909|     |      |
| Total        | 7  | 0.043868  |        |     |      |
3.3. Effect of parameter on fitness value

Based on the Figure 3, increasing value of crossover has the highest impact on reducing the fitness function in comparison to the parameters. However, the crossover parameter is well adequate in reducing fitness value when pairing with lower mutation rate as observed in Figure 4. This is due to that fact that functionality of the intermediate crossover operator allowed the expansion of variation offspring appear throughout the generations to increase and the crossover operator is highly dependent on the performance of the initial parents at a random sequence as the algorithm further evolves in generations [25].

![Main Effects Plot for Fitness Value](image)

**Figure 3.** Main effects of parameter against fitness value.

However, increasing the crossover constant drastically expands the quantity of offspring in the generations but the variation of offspring’s genes is constricted by the development of mutation operator as high crossover value contributes to more generations into the population, while low crossover may lead to stagnation and lower exploration rate [23]. Furthermore, crossover probability is positively correlated with mutation probability, however it is not proven significant [26]. Utilization of selection of population with crossover and mutation operators in optimization of the production of poly(lactic-co-glycolic acid) biodegradable micro-particles has showed that genetic algorithm parameters has influential effect in the area of food and process engineering [27].

As an independent factor, the mutation rate has lesser impact against the fitness value. Based on Figure 3 and 4, lower fitness value is achieved when paired with higher value of crossover rate and higher population size separately. High mutation rate has shown to produce better value of fitness faster but the population produce by the high mutation rate produced chaotic characteristic such as drastic convergences or slow convergences [28]. A considerable level of mutation rate is required as several individuals in the population may inherited different characteristics prior from their older generation. Thus, mutation increase a better opportunity in achieving global minima and avoid trapping in local minima in the search space [29]. Determination of optimum mutation rate is highly dependent on the neural network’s dataset and cannot be compared with the performance other applicant of various neural network.

Population size has less critical impact on fitness value based on Figure 3. The influence of both crossover and mutation operator influence the evolution and movement of the particles in the GA algorithm also relied on the population size; which is further known as disruptive effect [30]. Small population size often results in low information capacity and inaccurate sampling selection [21]. However, further studies have shown that population size has the most significant effect on genetic
algorithm performance in comparison to crossover and mutation probability [31]. GA parameter of population size is found be significant in optimization of fermentation medium in comparison to the GA parameters, as the increase of population size produces higher convergence rate to the optimum value.[32]

**Figure 4.** Interaction effects of parameters against fitness value.

3.4. Optimization of parameter using Factorial Design
Based on the dataset and the $2^k$ factorial design, the parameter is then optimized based on the minimization of the fitness function using the MINITAB statistical program (Figure 5). Constraints are placed for each parameter to ensure that program’s optimization search algorithm does not diverged out from the search space. The constraint of population size is based on study done [33] while the constraints of both crossover and mutation parameters are based on the numerical value available by the MATLAB program [25].

**Figure 5.** Optimization of GA parameters.
Table 4. Results of optimization GA parameters.

| Constraints | Population Size | Crossover | Mutation |
|-------------|-----------------|-----------|----------|
|             | 20-100          | 0.2-1.0   | 0.2-1.0  |
| Optimized Parameter | 100             | 0.2       | 1.0      |

Figure 6 illustrates the search pattern of the minimum fitness value and Table 4 summarized the results of the optimization GA parameters. The optimized GA parameters values are at maximum population size (100), minimum crossover rate (0.2) and maximum mutation rate (1.0). Optimization heavily relied on best combination value on all three parameters that able to achieve the objective function of the study. Therefore, the optimized parameters value would slightly contradict on independent parameter outcome. RSM used to identify the critical understanding on varying parameter combinations. RSM heavily relied on the experimental data accuracy and completing the experimental point assigned. The authors have further substantiated that failure to fulfil either both criteria often lead towards poor representation of the ANN-GA model in modelling electrocoagulation of copper from simulated wastewater [34].

![Figure 6](image-url)  
**Figure 6.** Performance of optimized GA parameter turning.

Comparison are made between GA-ANN and ANN by lowest MSE values and the highest R² values as illustrated in Figure 7 and Figure 8. Both designs shared the K-Fold cross validation method with the same architectural design. The results have shown GA-ANN’s MSE (0.033396) is lower than ANN’s MSE value (0.082263), which the GA-ANN’s R² value (0.88245) is higher than ANN (0.8499). High R² value and lower MSE value indicate the fitness level of the model [35]. Similar results of comparison has been in the evaluation and classification of potato quality [36] and defect detection of cherries [37], in which the use of GA has improved significantly on the ANN performance. Lower residual error represents a better fit of the model based on particular data set and signified higher R² value and lower MSE value [38].
Figure 7. Comparison of MSE between (a) ANN with K-Fold and (b) GA-ANN with K-Fold.

Figure 8. Comparison of R² value between (a) ANN with K-Fold and (b) GA-ANN with K-Fold.

4. Conclusion
In this study, a comparative study was performed between ANN and GA enhanced ANN to estimate their abilities in emulating the spray drying process of coconut milk powder under restricted parameters. The distinction difference between the two models is that during the training phase, the ANN model applied random weights initialization whereas the GA-ANN model applied a proposed weight initialization through an optimized parameter of GA learning. Based on the study, conclusions are drawn from the obtained results. Firstly, genetic algorithm parameters which are population size, crossover and mutation rates are optimized using RSM. The optimized GA parameters values are at maximum population size (100), minimum crossover rate (0.2) and maximum mutation rate (1.0). The optimized GA parameters is then applied in the development of the GA-ANN network as the networks applied genetic algorithm to determine the optimized weights in its neural network. Both models are then compared by placing importance of high R² and low MSE values. The results have shown GA-ANN’s MSE (0.033396) is lower than ANN’s MSE value (0.082263), which the GA-ANN’s R² value (0.88245)
is higher than ANN (0.8499). This shown that GA as a global search technique can be integrated in the development and enhancement of ANN.

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