IMPLEMENTING ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHMS TO SOLVE MODELING AND OPTIMISATION OF BIOGAS PRODUCTION

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ABSTRACT. This paper proposed a framework to model and optimises a biogas production using artificial neural networks and genetic algorithms. The intelligence computation was applied to achieve a better model and optimisation compared to a mathematical modeling. Two training approaches were used to train a set of neural networks design. The trained networks model predictions were used to generate a maximum biogas output assisted by genetic algorithms optimisation. The result showed that modeling accuracy with low error will not give a better yield. It also reported a 0.44% increase of maximum biogas yield from the published result.

Keywords: neural network, genetic algorithms, modeling, optimisation

INTRODUCTION

Modelling and optimisation were widely used in biological and chemical process domain to improve and increase efficiency of the process (Baş & Boyaci, 2007). The modelling was started with a simple one-factor-at-a-time method (Czitrom, 1999). The more complex statistical and mathematical models were later used for experimental design using partial or full factorial (Box, Hunter & Hunter, 2005). The design phase used several techniques to determine the inputs that correlate with the experiments such as central composite design and Taguchi (Cuevas, Tseng & Estrada, 2009). Statistical method was applied to the experiment results to generate the mathematical model. The most used method is response surface methodology (RSM) adopted by a great degree of researchers (Acherjee, Kuar, Mitra and Misra, 2012; Muhamad, Abdullah, Mohamad, Rahman & Kadhum, 2013; Meng & Yu, 2011; Noshadi, Amin & Parnas, 2012). The models were generated by the quadratic polynomial approximation function.

In recent years there were several attempts to use intelligence computation and machine learning in exchange of non-statistical methods. Artificial neural networks (ANN) and genetic algorithms (GA) were used in tandem. The main capabilities of ANN as a pattern recognition system were exploited to generate the model. In addition to its parallel processing prowess, it produced quicker and robust solution with less guessing and tried-and-true methods. The predicted model was optimised using genetic algorithms to find the optimal yield based on heuristic search inspired by brain functions.

The objectives of this paper are to propose a framework for modelling and optimisation and to compare the framework solution with the mathematical and statistical solution. ANN model accuracy also will be compared with different training approaches and networks topology.

BACKGROUND

Intelligence computation, such as ANN and GA, mimic different aspects of biological information processing for data modelling are useful in media optimisation (Singh, Khan, Khan & Tripathi, 2009). Lu, Lei, Xu, Shi & Xu (2011) were using the ANN and GA to optimise triterpenoid production and compared the RSM and ANN modelling. The results were reported an increase of prediction's accuracy and the triterpenoid production was higher using the ANN-GA model. The ANN hidden nodes were determined by several runs of ANN training of 1 to 6 hidden nodes to find the best network structure based on Huang, Mei and Jia (2006) studies.

Tian, Liu, Gao and Yao (2013) comparative studies of two different types of ANN gave different results in granulocyte colony-stimulating factor. The application of back-propagation (BP) and radial basis function (RBF) ANN were used to model the experiment and RBF model gave higher accuracy than the BP model. The BP model was fixed with 11 hidden neurons and hidden nodes of RBF were set with the number of training set cluster.

The study by Rivera, Costa, Maciel and Filho (2006) showed the higher optimal result using ANN modelling with optimisation by a real and a binary coded GA. The result was compared with a deterministic model which has the additional inputs from the 4 inputs of the ANN model. The ethyl alcohol production showed little improvement when using ANN model compared to the deterministic model although the ANN prediction model achieved a small prediction error.

All the studies reviewed so far, however, suffer from the fact that the ANN model was not always give the best yield of optimisation even though the model accuracy was high. This lead to trade-offs in the optimisation of ANN using Evolutionary Algorithms (EA) suggested by Nariman-Zadeh, Haghgoo and Jamali (2006) to overcome the problem.

METHODOLOGY

Biogas Datasets

The experiment datasets were taken from study by Zainol, Salihon and Abdul-Rahman (2009) to optimise an anaerobic sequencing batch reactor for biogas production. The experiment was done with 10 litre bioreactor seeded with anaerobic acclimatised banana stem sludge. The input sets are temperature, hydraulic retention time (HRT) and organic loading rate (OLR). Biogas evolved from the reactor was collected and was used as the output value.

Framework

The framework process flow was used to guide the modelling and optimising procedure of the biogas production experiment. It started with the normalisation of datasets based on the neural network requirement and design. The ANN design was set to 3 input nodes, 1 output nodes and several hidden nodes parameter. The hidden parameters were 2, 3, 5, and 10 nodes respectively. The ANN weights trainings were utilised the BP training method and particle swarm optimisation (PSO) training method. The two methods were compared for the gradient descent training versus the heuristic search method. After the trained ANN model was obtained, it will be used to predict the maximum of the biogas yield with the optimisation function of the GA. The GA parameter was set with 100 populations, 2 elite children and Roulette Wheel selection methods.

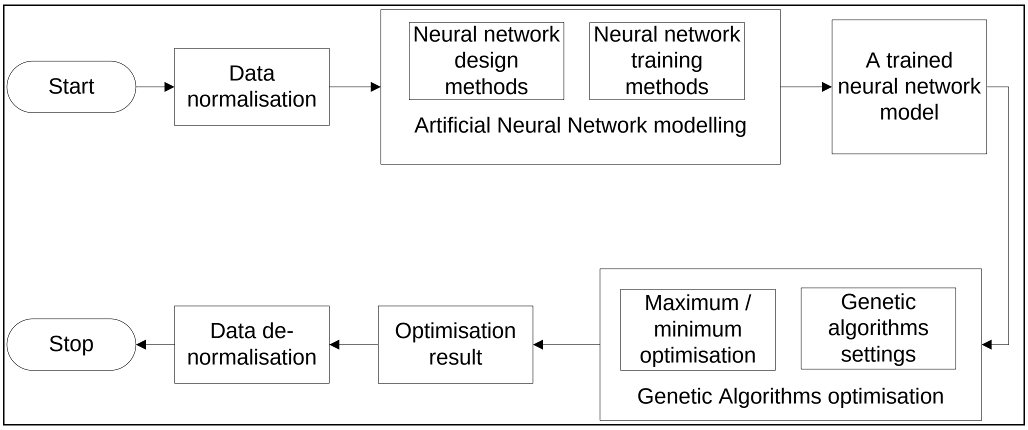

Figure 1. Process framework

Referring to Figure 1, the GA optimisation result was acquired before the de-normalised process was applied to it. The result was compared with the RSM method used by the engineering domain for model's accuracy and biogas yield maximum point.

Two neural networks training were employed to model the prediction system. BP training was applied to train a fix design neural network with the gradient descent capabilities to search suitable network weights. PSO training was used to overcome the local maxima problem of the weights training by the heuristic search capabilities of the PSO method. An evolutionary neural network was implemented to eliminate the need to set a number of hidden nodes. It used GA to evolve the best networks structure and weights.

RESULT AND DISCUSSION

Table 1. Predicted maximum of biogas

Method	Predicted maximum biogas (g/l)
RSM (Zainol et al., 2009)	1.9497
2-hidden neuron BP-GA	1.7507
3-hidden neuron BP-GA	2.0436
5-hidden neuron BP-GA	1.9583
10-hidden neuron BP-GA	1.9674
2-hidden neuron PSO-GA	1.8173
3-hidden neuron PSO-GA	1.9756
5-hidden neuron PSO-GA	1.8362
10-hidden neuron PSO-GA	1.9636
Evolutionary neural networks	1.8298

Based on the result of Zainol et al. (2009), the intelligence computation result was able to produce a better result in several cases shown in Table 1. The ANN modelling with 2 hidden neurons were failed to produce better result than the RSM modelling. With 3 and more hidden neurons, the maximum predicted were higher except the ANN model with 5 hidden neurons with PSO training. The ANN model outputs accuracy was high with small mean square error (MSE) to the targeted output. The lowest MSE was 0.0002 compared with RSM modelling was at 0.0005.

In contrast the ANN high accuracy was not always giving a better predicted maximum shown in the Figure 2 and Figure 3. PSO training gave less accuracy then the BP training but the model predicted on a par with the BP training model.

The 3 hidden neurons PSO training model was among the low accuracy group but it predicted a high biogas yield, with 1.9756 g/l of biogas. The maximum yield was produced by the BP training model with 3 hidden neurons topology. The application of evolutionary neural networks suggested networks architecture with 2 hidden layers with 3 hidden nodes and 1 hidden node respectively. The result was not par with both training methods because it is still in the preliminary stage.

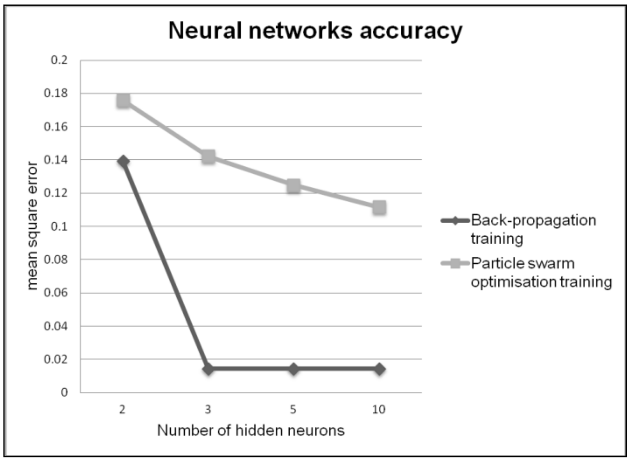

Figure 2. Neural networks accuracy

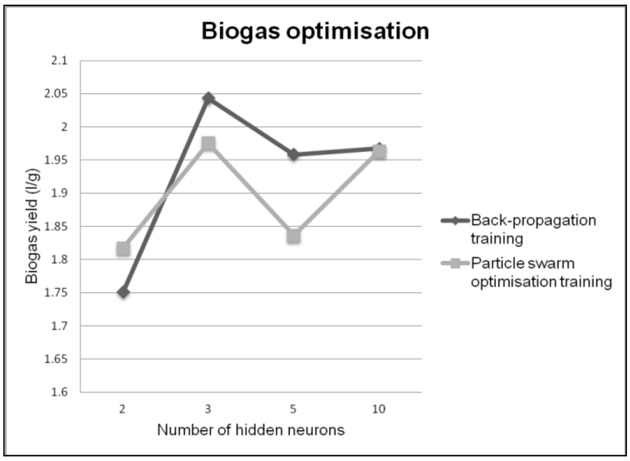

Figure 3. Biogas optimisation

The engineering domain requirement of the high biogas yield had to have a reasonable input point. Referring to Figure 4 and Figure 5, were the inputs maximum point for the predicted maximum of biogas respectively. Based on the temperature (energy requirement), low energy consumption was desired with less time to process (retention time). The ANN model with BP training and 5 hidden neurons were able to predict higher maximum with less energy and time. The maximum biogas yield by this model was 1.9583 g/l and the input criteria were 9.4709 days (HRT), 1.4241039 gTS/d.l (OLR) and 33.44 °C (temperature). This was an increase of 0.44% from the 1.9497 g/l biogas using RSM.

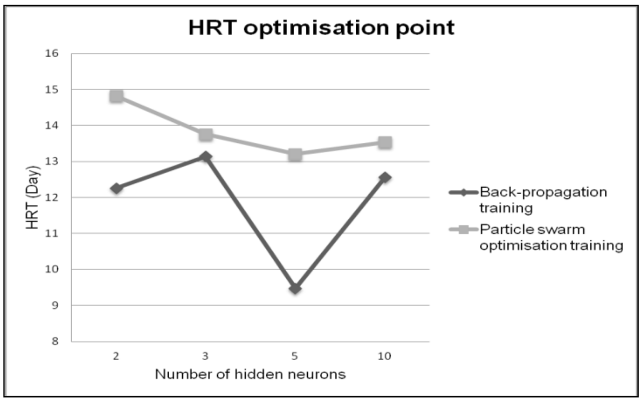

Figure 4. HRT optimisation point

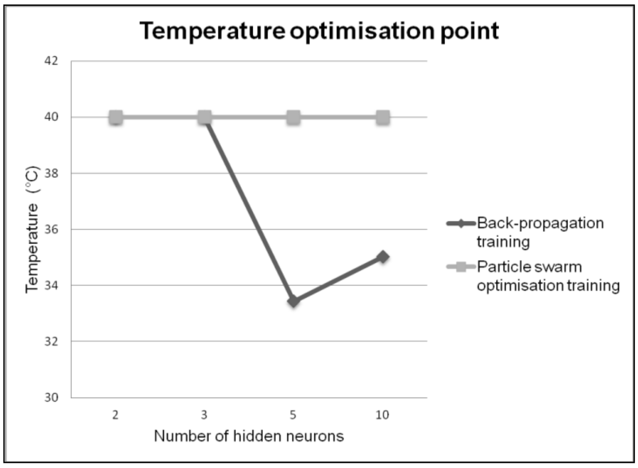

Figure 5. Temperature optimisation point

CONCLUSION

The proposed framework produced an improved result then the RSM method. It had a range of solution models with optimal inputs. Future modelling method will be able to automate the hidden nodes selection dilemma with the introduction of evolutionary approaches in designing and training of ANN.

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