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A proposed iteration optimization approach integrating backpropagation neural network with genetic algorithm

Han-Xiong Huang *, Jiong-Cheng Li, Cheng-Long Xiao

Lab for Micro Molding and Polymer Rheology, The Key Laboratory of Polymer Processing Engineering of the Ministry of Education, South China University of Technology, Guangzhou 510640, PR China

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ABSTRACT

An iteration optimization approach integrating backpropagation neural network (BPNN) with genetic algorithm (GA) is proposed. The main idea of the approach is that a BPNN model is first developed and trained using fewer learning samples, then the trained BPNN model is solved using GA in the feasible region to search the model optimum. The result of verification conducted based on this optimum is added as a new sample into the training pattern set to retrain the BPNN model. Four strategies are proposed in the approach to deal with the possible deficiency of prediction accuracy due to fewer training patterns used. Specifically, in training the BPNN model, the Bayesian regularization and modified Levenberg–Marquardt algorithms are applied to improve its generalization ability and convergence, respectively; elitist strategy is adopted and simulated annealing algorithm is embedded into the GA to improve its local searching ability. The proposed approach is then applied to optimize the thickness of blow molded polypropylene bellows used in cars. The results show that the optimal die gap profile can be obtained after three iterations. The thicknesses at nine teeth peaks of the bellow molded using the optimal gap profile fall into the desired range (0.7 ± 0.05 mm) and the usage of materials is reduced by 22%. More importantly, this optimal gap profile is obtained via only 23 times of experiments, which is far fewer than that needed in practical molding process. So the effectiveness of the proposed approach is demonstrated.

1. Introduction

Many engineering problems, such as system design, process control and prediction, and part manufacturing, are related to optimization. The purposes of the engineering optimizations can be generally summarized as follows: enhancing the system performance (Li & Yang, 2008; Wang, Zhao, Li, & Guan, 2011), increasing the process control and prediction precisions (Chang & Shih, 2010; Wang, Dong, & Sun, 2010), improving the product quality (Liu & Yang, 2008; Raja & Baskar, 2012), saving the cost (Lee & Lin, 2009; Wang, Wang, & Wang, 2013), etc. In engineering optimizations, a mathematical model is first developed for representing the quantitative relationship between the outputs and inputs of the investigated system or process, and then is solved in feasible region using an optimization algorithm to obtain the optimal process parameters.

However, precise explicit functions mapping the outputs and inputs of a system in engineering problems are often complex and nonlinear, and so quite difficult or even impossible to be deduced from some physical laws. For this reason, some approximation-based process modeling methods, including response surface methodology, radial basis function, Kriging model, and neural network (NN), are usually used to approximate the explicit functions in many engineering applications (Elsayed & Lacor, 2012; Gao & Wang, 2008; Huang, Li, Li, & Huang, 2011; Huang & Lu, 2005; Mirmohseni & Zavareh, 2011). Among these methods, NN is a synergistic representation of mathematical methods helpful in the modeling of nonlinear multivariate systems. The feature of the NN is its ability to capture complex nonlinear relationships between output and input patterns through appropriate learning. Among NN approaches, backpropagation neural network (BPNN) is the most classically and generally used training algorithm, and can provide effective solutions to industrial applications. BPNN is multilayer feed-forward neural network that is trained by the error BP algorithms. Although the BPNN is successful, it has some disadvantages. The algorithm is not guaranteed to find a global optimum and the convergence rate tends to be extremely low. In addition, the selection of the learning factor and inertial factor, which is usually determined by experience, affects its convergence. Genetic algorithm (GA) is a heuristic and stochastic optimization algorithm based on evolution theory and genetic principles. It is an aggressive

* Corresponding author. Tel./fax: +86 20 22236799.
E-mail address: mmhuang@scut.edu.cn (H.-X. Huang).

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search approach that quickly converges to find the optimal solution in a large solution domain by the genetic manipulations.

Various investigations have demonstrated that combining BPNN and GA is a helpful methodology to obtain desirable solutions to optimization problems (Ahmad, Jeenanunta, Chanvarasuth, & Komolavanij, 2014; Chatterjee & Bandopadhyay, 2012; Chen, Lai, Wang, & Hung, 2011; Chen et al., 2014; Cho, Moon, Kim, & Yun, 2012; Cook, Ragsdale, & Major, 2000; Dehghani, Sefti, Ameri, & Kaveh, 2008; Esmaeili & Dashtbayazi, 2014; Gossard, Lartigue, & Thellier, 2013; Ho & Chang, 2011; Huang & Huang, 2007; Irani & Nasimi, 2011; Kim & Han, 2003; Ko et al., 2009; Krishna, Rangajanardhaa, Hanumantha, & Sreenivasa, 2009; Mirarab, Sharifi, Ghayyem, & Mirarab, 2014; Nasseri, Asghari, & Abedini, 2008; Singh, Cooper, Blundell, Pratihar, & Gibbons, 2014; Sinha, Sikdar (Dey), Chattopadhyay, & Datta, 2013; Solenimani, Shoushtari, Mirza, & Salahi, 2013; Su, Yang, & Huang, 2011; Versace, Bhatt, Hinds, & Shiffer, 2004; Wang et al., 2010; Yuen, Wong, Qian, Chan, & Fung, 2009). For example, Kim and Han (2003) proposed a hybrid model composed of BPNN and GA, in which the GA globally searches and seeks an optimal or near-optimal BPNN topology. Huang and Huang (2007) proposed a hybrid method consisting of finite element method, BPNN and GA to optimize the parison thickness distribution for an extrusion blow molded plastics part with required thickness distribution. The results showed that the proposed method can be used to effectively obtain the optimal parison thickness distribution. Dehghani et al. (2008) used GA to optimize the connection weights, network architecture and learning rules of BPNN model. Ko et al. (2009) investigated the process modeling for the growth rate in pulsed laser deposition-grown ZnO thin films using BPNN and GA. The results showed that this modeling methodology can explain the characteristics of the thin film growth mechanism varying with process conditions. Wang et al. (2010) coupled a BPNN with a GA to predict the saturates of sour vacuum gas oil. The study showed that the GA can find the optimal architecture of the NN and the parameters of the BP algorithm. Ho and Chang (2011) used a GA in the BPNN to find the optimal parameters to investigate the promoted effectiveness of predicting platelet transfusion requirements for acute myeloblastic leukemia patients. Irani and Nasimi (2011) presented a GA evolved BPNN, which can improve the reliability and predictability of BPNN. Each initial weight of the gradient descent-based BPNN was selected by a standard GA and the fitness of the GA was determined by the BPNN. The genetic operators and parameters were carefully designed and set, avoiding premature convergence and permutation problems. The methodology combines the local searching ability of the gradient decent method with the global searching ability of the GA. Su et al. (2011) found that better initial weight/bias for the NN can be calculated by the GA. Chatterjee and Bandopadhyay (2012) used a GA for the selection of BPNN parameters to forecast the reliability of a load–haul–dump machine. In the work of Esmaeili and Dashtbayazi (2014), a BPNN model was used for predicting the characteristics of the prepared Al/SiC nanocomposite, and then GA was applied to optimize the process parameters. The results showed that the combination of the BPNN and GA would make good on appropriate use of data for predicting and optimizing preferred parameters in materials processing technology. Singh et al. (2014) applied a GA to enhance the prediction accuracy of BPNN by altering its topology. Mirarab et al. (2014) performed an optimization procedure based on GA to select the best BPNN architecture and determine the optimum neuron numbers in the hidden layer of the BPNN.

As a combined prediction-optimization approach, the hybrid BPNN–GA model processes excellent performance since it combines the inherent merits of BPNN (i.e. accurate nonlinear data fitting or regression capabilities) and GA (i.e. efficient and parallel global searching ability). From the foregoing, the optimization strategy coupling BPNN with GA is a very effective approach to solve engineering optimization problems. Moreover, following two main aspects are covered in applying GA into BPNN. One is to optimize the topological structure of the network, and the other is to optimize some parameters of the network. However, there are

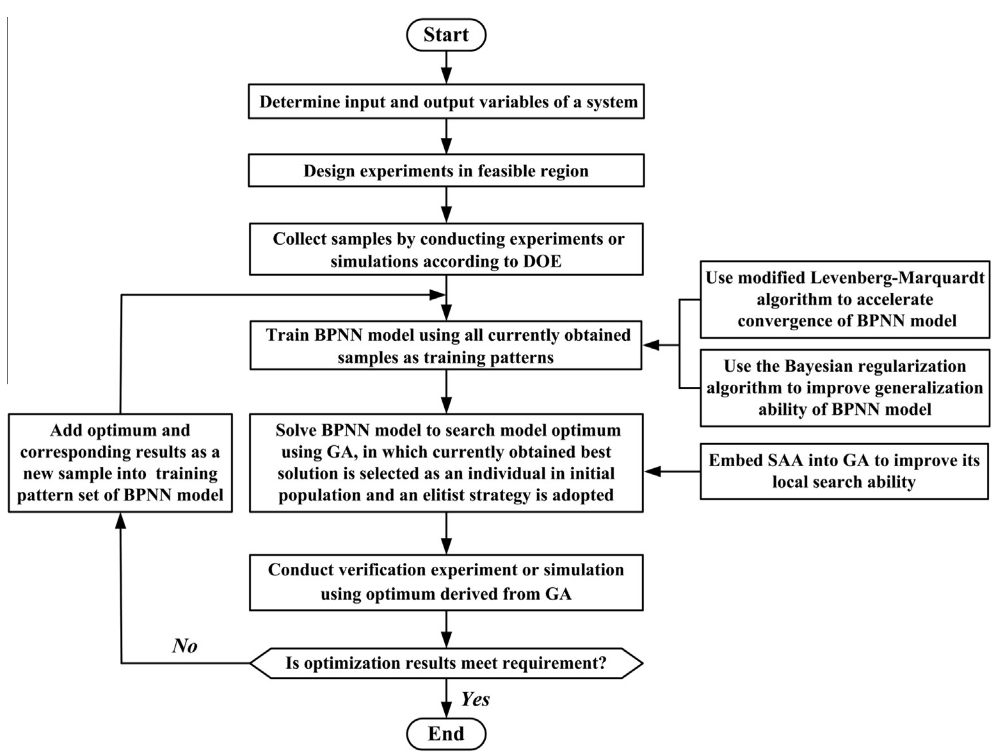

Fig. 1. Flow chart of proposed iteration optimization approach integrating BPNN with GA in this work.