Modeling and Optimizing Tensile Strength and Yield Point on Steel Bar by Artificial Neural Network with Evolutionary Algorithm

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EXTENDED ABSTRACT

The artificial neural network (ANN) with Taguchi-genetic evolutionary algorithm (TGEA) is combined to construct the steel bar model and optimize the factors of steel bar. The TGEA in the ANN is to find the most suitable weight of neuron combination and the optimal combination of influencing factors. In the experiment, the steel bar model is constructed by the TGEA-based ANN, and the TGEA is utilized to optimize all process parameters.

In recent years, steel bars have been widely used in buildings and bridges. However, corrosion attack in reinforcing steel bars often causes early deterioration and failure of concrete structures. Therefore, the resistant of earthquake of steel bars becomes an important issue. Recently, due to the development of computational intelligence techniques, the ANN has been successfully applied in the many fields [1-3]. The TGEA was first proposed by Tsai et al. [4], and was confirmed as a useful tool for parameter design optimization of engineering problems [5]. The TGEA explores the best settings of parameters combination and improves the performance characteristic by using orthogonal array and signal-to-noise ratio [6].

The chemical composition is the key technology of the steel bars, but traditional steel bar manufacture process is followed by the setting procedure and the experience of engineer. However, the Chinese national standards 560 (CNS560) stipulate the important chemical composition of steel bars including carbon, silicon, manganese, phosphorus, sulfur, and carbon equivalent. Cadoni et al. [7] and Sato et al. [8] indicated that the compositions affect the yield point (*YP*) and tensile strength (*TS*) such as carbon, sulfur, phosphorus, silicon, manganese, carbon equivalent, copper, etc. Fig. 1 shows the relationship between *YP* and *TS* for steel bars.

In this study, the proposed TGEA-based ANN combines the three-layer five-hidden-node ANN and the TGEA to construct the model for the chemical composition of steel bar. Ten chemical composition are the carbon (C%), silicon (Si%), manganese (Mn%), phosphorus (P%), sulfur (S%), copper (Cu%), nickel (Ni%), chrome (Cr%), molybdenum (Mo%), and vanadium (V%) as the inputs of TGEA-based ANN for CCSB, and two outputs are *YP* (kgf/mm^2) and *TS* (kgf/mm^2). The *YP* and *TS* are transformed to the single value according to the characteristic of larger-the-better, shown in Eq. (1). The output value of the ANN is regarded as the fitness function of the TGEA in the study.

$$\eta = -10\log\left(\frac{1}{n}\sum_{t=1}^{n}\frac{1}{y_t^2}\right), \tag{1}$$

Each input value is normalized before importing its value into the training process. The data are applied to evaluate the performance of TGEA-based ANN. For each output, the training process seeks for the smallest root mean squared error (RMSE), which can be represented as

$$J = \left[\sum_{m=1}^{n}\frac{\left(R_m - O_m\right)^2}{n}\right]^{\frac{1}{2}} \tag{2}$$

where n indicates the number of training data items, R_m is the actual output value, and O_m denotes the predicted output value.

The practical application of the proposed method was demonstrated in the engineering design problem of CCSB. In the experiment, 800 data are used for training the TGEA-based ANN model, and 200 data are used for testing the performance of the model. Table I shows the data range of the input values of training and test data. The performance evaluation indexes for mechanical properties are *YP* and *TS*. Table II shows the average RMSE of training data and test data obtained by conventional BP and the TGEA-based ANN for building the model of CCSB. Finally, the TGEA was used to optimize values of ten inputs. The major contribution of this study is to use the TGEA approach to enhance the data training ability of three-layer ANN for CCSB. Therefore, for designing chemical composition of steel bar, the proposed TGEA-based ANN is a useful tool for engineering problem optimization.

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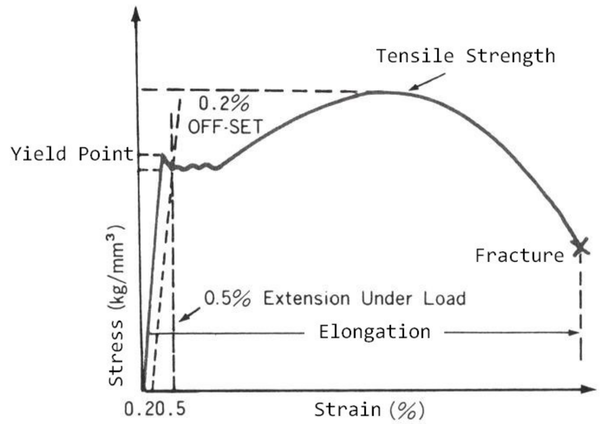

Figure 1. The relationship of yield point and tensile strength for steel bars [9][10].

Table I. Range of input values of training and test data.

Parameter	*Range*	
	Min.	*Max.*
C (%)	0.1903	0.2478
Si (%)	0.0509	0.1995
Mn (%)	0.6000	0.7975
P (%)	0.0165	0.0488
S (%)	0.0700	0.0484
Cu (%)	0.1699	0.4486
Ni (%)	0.0584	0.1496
Cr (%)	0.0842	0.2454
Mo (%)	0.0118	00587
V (%)	0.0030	0.0078

Table II. Comparison of root mean square error (RMSE) for conventional BP and TGEA-based ANN in building the model for the chemical composition of steel bar.

Model	RMSE			
	Training data set		*Test data set*	
	TS	*YP*	*TS*	*YP*
Conventional BP	1.5400	1.4000	2.2551	1.8305
TGEA-based ANN	1.4839	1.2101	2.1723	1.6769