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# The artificial neural network prediction algorithm research of rail-gun current and armature speed based on B-dot probes array

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ABSTRACT

In this paper, based on the advantages of artificial neural network, such as good tolerance of data noise, strong ability of nonlinear mapping, multi-dimensional input variables, fast operation, low error, etc., a method of using artificial neural network for data prediction is proposed for the research of rail-gun. The results show that it is feasible to use the Back Propagation Neural Network, the Radial Basis Function Neural Network and the General Regression Neural Network to realize the method of prediction and simulation of the rail-gun current and the armature speed curve through relevant parameters. The General Regression Neural Network has superiority in error performance and time cost of neural network training and simulation.



## 1. Introduction

Rail-gun, using the electromagnetic launch technology, releases the electromagnetic energy provided by the energy system in the form of a pulsed high current, so that the armature is able to propel the projectile to accelerate to a high speed of more than 3 km/s and achieve the target damage mission. The performance of rail-gun is a center part of the rail-gun research. The direct indicator of the damage capability of rail-gun is the speed of the projectile, in other words, the armature speed. The study of the armature speed during the launch stage can help to improve the configuration of the energy system. The study of the rail-gun current can help to improve the overall coupling condition of the electromagnetic launch device and the energy system operation. Therefore, the research on the above two parameters is of high practical value and significance [1].

At present, parts of the research methods for rail-gun performance parameters use the form of simulation and parameter analysis. Specifically, most of them use statistical fitting, formula derivation, modeling of a simplified circuit model, and parameter performance simulation [2–4]. The drawback of the kind of research is that the mathematical model or circuit model is too idealized, and the actual equipment usually suffer from some inevitable damage, such as planing, armature erosion and grooving [5]. The above damages lead to the constant change of launch environment for the armature, and the decline of the applicability and guiding significance of idealized model simulation and parameter analysis conclusions for actual experiment. The corresponding solution method generally needs to establish additional models and parameters, which is tedious and not universal. On the other hand, rail-gun launch current and the armature speed are affected by many factors, and the theoretical research is difficult. For the measurement equipment, since the launch process of the rail-gun is ephemeral, which is generally in the microsecond level, the measurement equipment is required to be high resolution and stability, and this increases research costs.

Based on the above reasons, this paper tries to utilize the artificial neural network in order to propose a new method to predict and simulate the rail-gun current and armature speed waveform.

## 2. Artificial neural network

### 2.1. Introduction of neural network

The essence of the prediction and simulation tasks we mentioned is function approximation, because the objects that need to be predicted are unknown nonlinear waveforms. Artificial neural network simulates the computational properties of the brain (Schalkoff, 1997), for example, adaptative, data noise, and tolerance of connection errors between neurons [6]. Artificial neural

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networks are widely used in image recognition, function approximation, prediction, optimization, and control. Among them, in the area of function approximation, multilayer neural networks are considered to be able to approximate arbitrary functions with arbitrary precision.

The basic idea of function approximation is that a single complex function can be represented using multiple simple functions. The function approximation ability of neural networks is reflected in its nonlinear mapping ability. The superiority of the application of neural network for function approximation can be reflected in the case that the data characteristics are unclear, and the data are fuzzy or contains noise and nonlinearity. A variety of neural networks can be used to complete the task of function approximation. At present, the widely used and approved networks in this field mainly include BP neural network, RBF neural network and GR neural network, due to their abilities of fast training, good approximation performance and other characteristics. Therefore, this paper tries to use the above three neural networks to complete the prediction and simulation tasks of the rail-gun current and armature speed.

### 2.2. Back propagation neural network

The most widely used neural network is the Back Propagation Neural Network (BPNN). The structure of this neural network can be divided into three parts: input layer, hidden layer, and output layer, as shown in Fig. 1. Among them, the input layer receives data variables that need to be processed, and the output layer outputs the results of data processing. The hidden layer can be visualized as the scheme and flow of data processing of the neural network. The number of input layer nodes is related to the dimension of input data, and the output layer is the same. The hidden layer can have several layers. The configuration of nodes at each layer is unlimited. Both layers and nodes of each layer affect the performance of the BPNN, and they can be changed according to the actual requirements. The learning rule of BPNN generally adopts the gradient descent. Back propagation represents that the error of the output of the output layer and the sample output passes to the input layer through the hidden layer. Thereby it continuously modifying the connection relationship between the different layers, which finally achieves that error is less than the set threshold. The Back Propagation Neural Network can be applied to function approximation, classification, prediction, control, pattern recognition and so on.

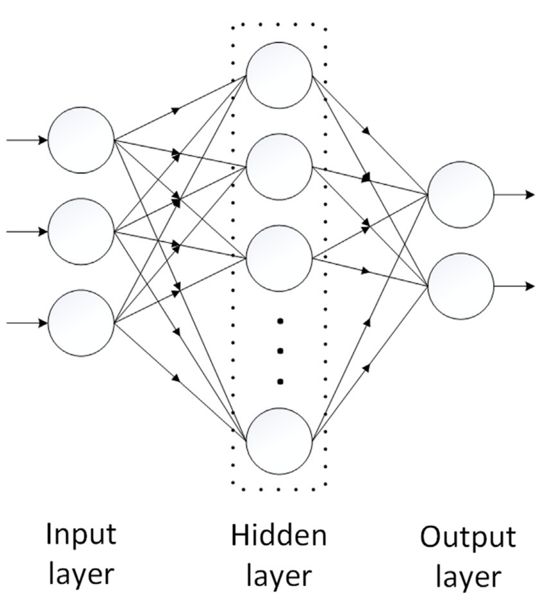


**Fig. 1.** Structure schematic of Back Propagation Neural Network.

### 2.3. Radial basis function neural network

Radial Basis Function Neural Network (RBFNN) is a special case of Back Propagation Neural Network. The idea of RBF neural network is to transform data into high-dimensional space, making it linearly separable in high-dimensional space. The structure of RBFNN is similar to BPNN, except that its hidden layer is fixed to only 1 layer. And the transfer function used by its hidden layer node is a radial basis function, such as Gaussian function, shown as the Eq. (1), while the hidden layer node of the BPNN generally adopts the sigmoid function as the transfer function. In Eq. (1), x represents the input, $C_k$ is the center of the Gaussian function, $||x - C_k||$ is the Euclidean norm, and $\sigma$ is the Gaussian function variance, which controls the radial range of the function.

$$\Phi_k(x) = \exp\left(-\frac{||x - C_k||^2}{2\sigma_k^2}\right) \tag{1}$$

The radial basis function is a local activation function. When the input is in the center of the function, the output of the function is the largest; when the input is far from the center of the function, the output of the function is rapidly attenuated. In the training process of RBFNN, the function center and function radial range are affected by the learning sample.

Structurally, the number of hidden layers of RBFNN is less than that of BPNN, which causes that less weight of RBFNN needed to be updated during training than BPNN. In terms of neural network learning, the BPNN belongs to the global approximation network. The BPNN needs to determine the connection weights and thresholds between nodes in different layers, which makes it easy to fall into a local minimum and the network convergence speed is slow. The RBFNN belongs to the local approximation network. When the input is far from the center of the function, the node does not respond. This way of learning makes the training efficiency and approximation ability of RBFNN both perform better than BP neural network.

### 2.4. General regression neural network

General Regression Neural Network (GRNN) is an improved form of the RBFNN. It is based on non-parametric regression. According to the principle of maximum probability, a density function is used for output prediction. GRNN is divided into four layers in structure, input layer, pattern layer, summation layer, and output layer. It is worth noting that it is the number of pattern layer nodes is equal to the number of learning samples, and the transfer function used by the pattern layer nodes is shown in Eq. (2), where X is the input and Xi is the i-th node for the corresponding learning sample, $\sigma$ is a smoothing factor, and the output of the function is a measure of the distance between the input pattern and each stored training pattern. The nodes of the GRNN summing layer have two work types. The first is the arithmetic summation of the outputs of all pattern layer nodes, and the second is the weighted summation of the outputs of all pattern layer nodes. Since GRNN is a special form of RBF neural network, it also has the advantages of RBFNN. In addition, it is of good global convergence. GRNN is suitable for solving non-linear approximation problems, and has extensive applications in signal analysis, structural analysis, and control science [7].

$$P_i = \exp\left[\frac{-(X - X_i)^T(X - X_i)}{2\sigma^2}\right] \quad i = 1, 2, \ldots, n \tag{2}$$