Annals of Electrical and Electronic Engineering, 2(6) 2019, Pages: 1-5

Published by IASE

Annals of Electrical and Electronic Engineering

Journal homepage: www.aeeej.org

Utilizing multi-layer perceptron in fault detection of linear motors in magnetic levitation systems

R. F. Hashim *, S. F. Hassan

Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Shah Alam 40450, Malaysia

ARTICLE INFO

Article history:
Received 20 January 2019
Received in revised form
5 April 2019
Accepted 20 April 2019

Keywords:
Optimization
MAGLEV
CE 512
ICA
MLP

ABSTRACT

The magnetic levitation system (MAGLEV) has achieved high progress around the world. The commercial operation of the China high-speed MAGLEV line as well as Japan MAGLEV system, symbols the Electromagnet Suspension (EMS) system is stepping into the commercial application phase. In these systems, the occurrence of a little fault can lead to a humanitarian catastrophe. Therefore the early detection of these faults can prevent a humanitarian catastrophe. In this paper, a hybrid system based on artificial neural networks is proposed for early fault detection in MAGLEV systems. The proposed system includes three main sections: the model section, the classifier section, and optimization section. In the model section, we used the CE 512 standard model. In the classifier section, we used the MLP neural network. In the MLP neural network, the number of hidden layers and the number of neurons in hidden layers have a high effect on the performance of the network. Therefore in the proposed system, we used the imperialist competitive algorithm (ICA) to find the optimum values of these parameters. The proposed method is tested on CE 512 system model and the simulation results show that the proposed method has excellent accuracy in the detection of faults.

1. Introduction

With the application of maglev train, the dynamics properties of maglev system have attracted great attention of many researchers. Many excellent and interesting results have been obtained (Abdioglu et al., 2015; Bächle et al., 2013). The maglev system is a complicated system with machinery, controllers and electromagnetic elements integrated together. In MAGLEV systems, the occurrence of little fault, can led to humanitarian catastrophe. Therefore the early detection of these fault can prevent from humanitarian catastrophe (Abdioglu et al., 2015; Sun et al., 2013).

In last decades, some computer aided detection (CAD) systems have been merged to apply in pattern recognition and fault detection area. The fuzzy logic concept is one of the most popular of these computer aided detection systems. In fuzzy logic concept, one human expert is needed to extract fuzzy rules. This type of computer aided detection system has good performance in cases that are very complicated. But this system is not applicable permanently. Because with little change in control plant, all fuzzy rules loss their credit. In this situation, the human expert is needed to re-extract the new fuzzy rules for new system. Therefore the human expert is necessary permanently. In MAGLEV systems, we need a powerful monitoring system to monitor and detect any fault in early stages. Therefore fuzzy logic based monitoring system cannot satisfy powerful monitoring system's feature (Addeh, 2014).

Another computer aided detection system that has been applied vastly is support vector machine. The support vector machine good characteristics in binary pattern recognition problems. The support vector machine can only classify two patterns from each other. Therefore in problems with multiple patterns, we need to multiple support vector machine. The training algorithm of support vector machine is very complicated and need to high time and volume of computations. Furthermore the free parameters of support vector machine have high effect on its performance. These parameters are the type of kernel function, the value of sigma, the initial bias values and the penalty factor (Addeh, 2014).

Another computer aided detection system that has been applied vastly in different areas is artificial neural networks. The artificial neural networks have different types such as radial basis function network (RBFNN), probabilistic neural network (PNN), recursive networks, competitive networks and multi-layer Perceptron neural networks (MLPNN). The radial basis function network has goof features in function approximation and pattern recognition. In the radial basis function network, the value of spread and the number of radial functions have high effect on performance of network. The probabilistic neural network has excellent features in function approximation problems. The training algorithm of probabilistic neural network is straightforward. The MLP neural network has good capabilities in pattern recognition and fault detection. In this study we used MLP neural network as classifier (Addeh, 2014). As mentioned, in MLP neural network the number of hidden layers and number of neurons in hidden layers have high effect on performance of network. Therefore in the proposed system, we used imperialist competitive algorithm to find the optimum values of these parameters. The details of proposed method is described in next sections. The second section presents the CE 512 standard model for magnetic levitation system. The needed concepts such as MLP neural network and optimization algorithm is presented in third section. The proposed method and obtained simulation results are described by details in forth section. The final results of performed simulations and conclusion of paper is presented in fifth section.

* *Corresponding Author.*
Email Address: r.f.hashim@hotmail.com (R. F. Hashim)
https://doi.org/10.21833/AEEE.2019.06.001

2. CE 512 standard model

The Magnetic levitation system is shown on Fig. 1. It consists of a Magnetic levitation education model, laboratory card and control computer. The essence of this system is keep levitate the steel ball in the air by using electromagnetic force, which is produced from electric current going through the coil with soft magnetic core (Zhou et al., 2010; Wen et al., 2015).

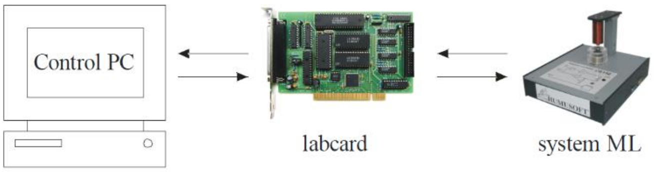

Fig. 1. Magnetic levitation system.

The mathematical model of the Magnetic levitation system is divided into five subsystems, namely ball and coil, power amplified, position sensor, and A/D and D/A converters (Fig. 2).

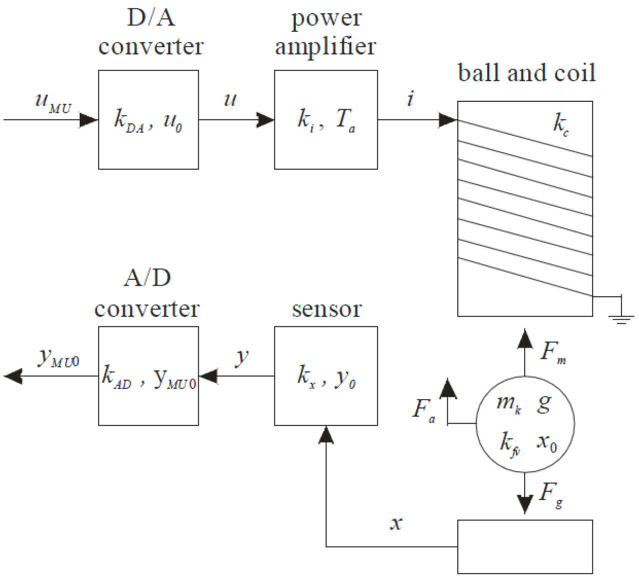

Fig. 2. Magnetic levitation model.

The mathematical model of the ball and coil subsystem is based on the balance of forces acting on the ball:

$$F_a = F_m - F_g \tag{1}$$

where

F_a – accelerationforce[N]
F_m – electromagneticforce[N]
F_g – gravityforce[N]

After substituting relationship for each power in Eq. 1 and adding a damping force F_{fv} is obtained mathematical model of the ball and coil subsystem, which is described by nonlinear differential equation of second order:

$$m_k\ddot{x}(t) - k_{fv}\dot{x}(t) = \frac{i(t)^2 k_c}{(x(t)-x_0)^2} - m_k g \tag{2}$$

where

$i(t)$ - electric current (A)
$x(t)$ - ball position (m)
m_k- mass of ball (kg)
k_c- coil constant (A/V)
X_0- coil offset (m)
g - gravity constant $(\frac{m}{s^2})$
k_{fv}- damping constant $(\frac{N}{m.s})$

By electric current $i(t)$, which is generated from the power amplified. The power amplified is designed as a source of constant current and is described transfer function F_z:

$$F_z = \frac{I(s)}{U(s)} = \frac{K_i}{T_a s+1} \tag{3}$$

where

$I(s)$ - image of electric current $i(t)$
$U(s)$ - image of input voltage $u(t)$
k_i- coil and amplified gain (A/V)
T_a - coil and amplified time constant (s)

An inductive sensor is used to determine the ball position, which is approximated by a linear equation:

$$y(t) = k_x x(t) + y_0 \tag{4}$$

where

$y(t)$ - sensor output voltage (V)
$x(t)$ - ball position (m)
k_x- sensor gain (V/m)
y_0 - sensor offset (V)

The signal incoming from laboratory card resp. from inductive sensor for communication with surrounding is necessary adjusted for further processing and therefore D/A resp. A/D converter is added into mathematical model. The converters can be described by linear equations (Zhou et al., 2010):

$$\frac{D}{A}\,converter\ u(t) = K_{DA}U_{MU}(t) - U_0 \tag{5}$$

$$\frac{A}{D}\,\text{converter}\ y_{MU}(t) = K_{DA}y(t) - y_{MU0} \tag{6}$$

where

$u(t)$ - converter output voltage (V)
$u_{MU}(t)$- converter input voltage (MU)
k_{DA}- converter gain (V/MU)
u_0 - converter offset (V)
$y_{MU}(t)$ - converter output voltage (MU)
$y(t)$ - converter input voltage (V)
k_{AD}- converter gain (MU/V)
y_{MU0} - converter offset (MU)

Based on Eq. 2 to Eq. 6, which describe mathematical model of the Magnetic levitation system was programmed simulation scheme of the Magnetic levitation nonlinear model (Fig. 3).

Since the Magnetic levitation system is unstable in open loop, physical analysis of the simulation model was carried in a feedback control structure with defined reference signal y_{ref} and experimental proposed PID parameters (Wen et al., 2015). The result graph (Fig. 4) shows the possibility of further use of Magnetic levitation model in the control structure using exact feedback linearization method (Fig. 5).

3. Needed concepts

3.1. MLP neural networks

The main structure of MLP neural network is illustrated in Fig. 6. The MLP neural network has one input layer, one or more hidden layer and one output layer. The efficient training algorithm is the main problem in MLP neural network. The training algorithm is need to find the best weights and biases.

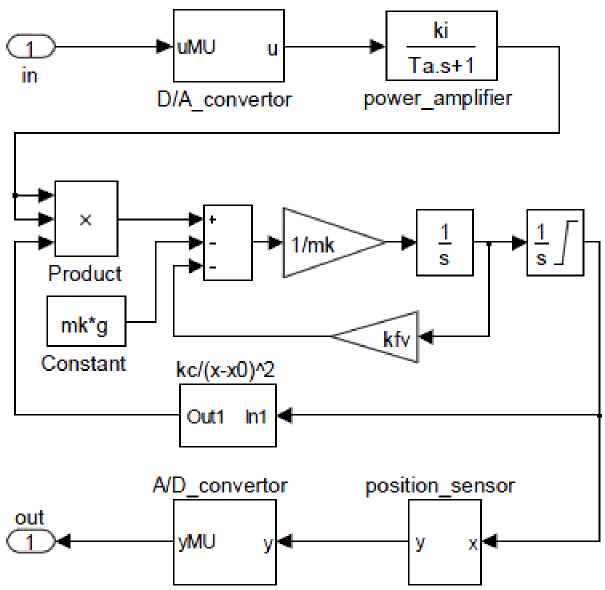

Fig. 3. Simulation scheme of magnetic levitation model.

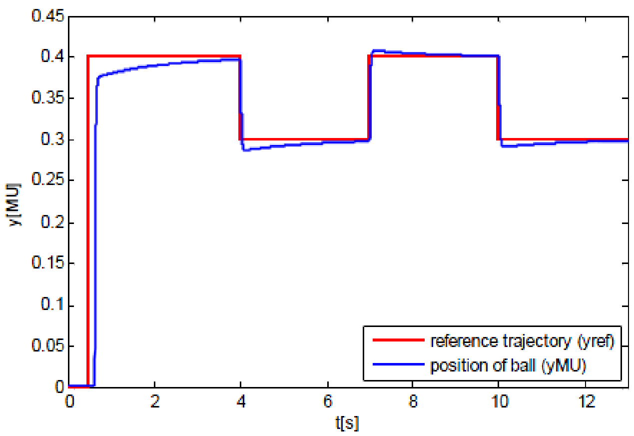

Fig. 4. Physical analysis of the magnetic levitation simulation model.

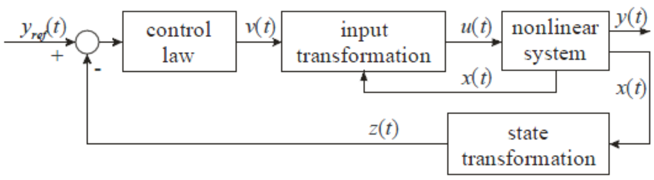

Fig. 5. Control structure using exact feedback linearization method.

Back propagation (BP) is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by designer. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities.

Standard back propagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. The term back propagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. There are a number of variations on the basic algorithm that are based on other standard optimization techniques, such as conjugate gradient and Newton methods. More details regarding the training algorithm for MLP neural network can be found in Wen et al. (2015) and Li et al. (2013).

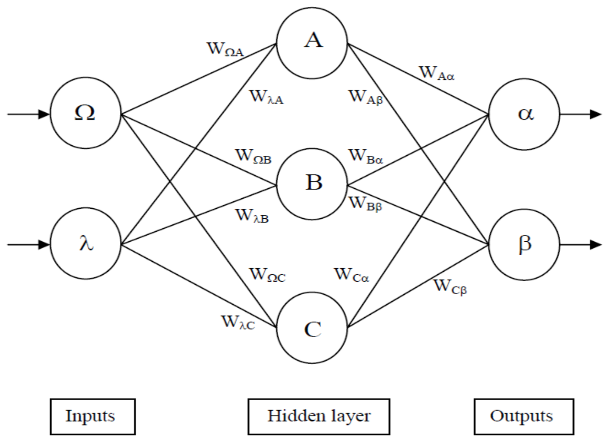

Fig. 6. MLP neural network main architecture.

3.2. Optimization algorithm

The imperialist competitive algorithm is used in the proposed method to optimize the structure of MLP neural network. The imperialist competitive algorithm is an optimization algorithm that inspired from politician behavior of human. Like other nature based optimization algorithms, this algorithm starts with random initial population. The initial population is composed from several countries. These countries are look like the particles in particle swarm optimization algorithm or bee in bee's algorithm. The initial countries are made randomly in search space. The competitive process is start among these countries. The best countries among these countries selected as imperialist. Each imperialist has some colony. Each colony made from some countries. In Fig. 7 the main structure of imperialist competitive algorithm is illustrated.

The imperialist competitive algorithm has some main operators such as evolution, imperialist competition, movement and other operators. More details regarding the imperialist competitive algorithm can be found in Enayatifar et al. (2013) and Hosseini and Al Khaled (2014).

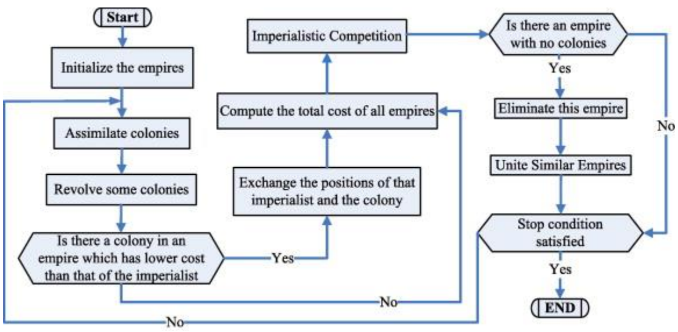

Fig. 7. The main structure of imperialist competitive algorithm.

4. Proposed method and simulation results

In this the proposed method and simulation results are presented. The following sub-section the proposed method is presented.

4.1. Proposed method

In MLP neural network, number of hidden layers and the number of neurons in hidden layers have very vital role in its performance. For this purpose in this study we proposed an intelligent method to select the optimal value of these parameters automatically. In the proposed method, ICA is used as optimization algorithm. In the proposed method, each county determines the number of hidden layers and the number of neurons in hidden layers. In this country, we have four variables. The first variable shows the number layers. Based on this variable, the second, third and fourth variables show the number of neurons in hidden layers. The sample country is shown in Fig. 8. In this method, we used recognition accuracy as objective function. The best country has highest recognition accuracy.

$$sample\ country = [x_1 x_2 x_3 x_4]$$
or
$$sample\ country = [No.of\ hidden\ layers, No.of\ neurons\ in\ 1^{th}\ layer....., No.of\ neurons\ in\ 3^{th}\ layer]$$

Fig. 8. Sample country in the proposed method.

4.2. Simulation results

In this study we consider three faults that may be occurred in magnetic levitation system. These faults are voltage oscillation fault, position sensor fault and power amplifier fault. The normal trajectory of levitation system is shown in Fig. 9. Also the plot of other faults are illustrated in Figs. 10-12. In Fig. 13 the plot of all states are shown. It can be seen from this figures that these states are similar together and the classification of these patterns are very difficult problem.

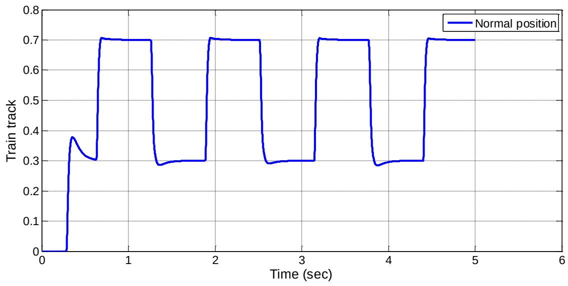

Fig. 9. The normal trajectory of levitation system.

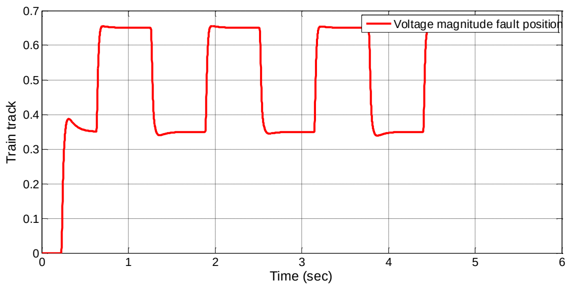

Fig. 10. The trajectory of levitation system in presence of voltage fault.

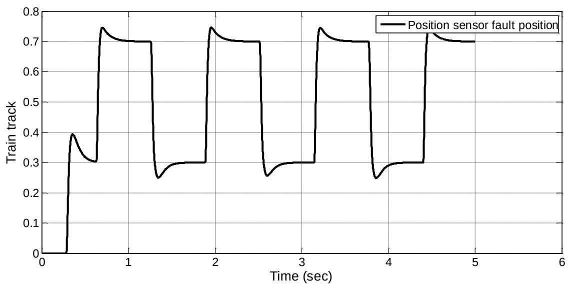

Fig. 11. The trajectory of levitation system in presence of position sensor fault.

In first experiment, the number of hidden layers and corresponding neurons are selected by trial and error. The structure of MLP network is shown in Table 1. Also the obtained results are listed in Tables 2 and Table 3. Also the effect of number of neurons in hidden layer is shown in Fig. 14. It can be seen that the number of neurons in hidden layer has high effect on recognition accuracy of MLP network. Also the training convergence of training algorithm is shown in Fig. 15. It can be seen that the proposed training algorithm has good convergence speed.

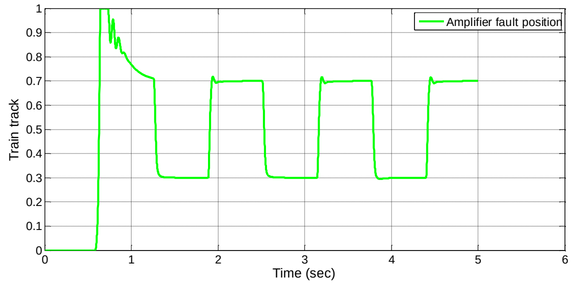

Fig. 12. The trajectory of levitation system in presence of power amplifier fault.

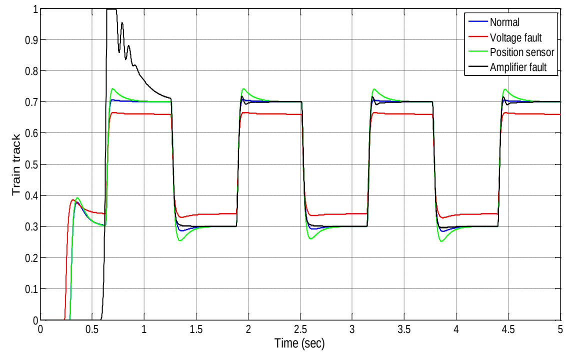

Fig. 13. The trajectory of levitation system in presence of voltage different states.

Table 1
The structure of MLP network.

Number of hidden layers	1 or 2
Number of neurons in output layer	4
Training algorithm	RPROP
Initial weights	Random
Transfer function (hidden layer)	Tangent-sigmoid
Transfer function (output layer)	Purelin

In next experiment, we used ICA to find the best value of free parameters. The control parameters of ICA are listed in Table 4. These parameters are selected based on trial and error and extensive simulations. The obtained results are listed in Table 5. It can be seen that optimization improves the performance of MLP network significantly.

5. Conclusion

In this paper was presented fault detection method for Magnetic levitation system. We used MLPNN as fault detector. It can be found that the training algorithm has very high effect on MLP performance. Also the number of neurons in hidden layer is important parameter in MLPNN. By extensive simulation we found that MLPNN with RPROP training algorithm has best accuracy. In order to enhance the performance of MLP neural network, the imperialist competitive algorithm is applied to select the best structure of network. Simulation results show that the optimization algorithm can improve the recognition accuracy significantly.

Table 2
Obtained results with one hidden layer.

Number of neurons in hidden layer	Recognition accuracy (%)
4	94.5
5	95.2
6	95.3
7	95.4
8	96.3
9	97.7
10	98.1
11	98.2
12	98.4
13	98.4
14	98.8
15	98.2
16	98.3
17	98.1
18	98.4
19	98.5
20	98.2
21	97.6
22	97.9
23	98
24	98.1
25	97.7
26	97.6
27	98.1
28	97.8
29	96.5
30	96.4

Table 3
The obtained results with 2 hidden layers.

Number of neurons		Recognition accuracy (%)
Layer 1	Layer 2	
10	16	98.5
15	18	98.9
17	20	98.4
18	21	98.5

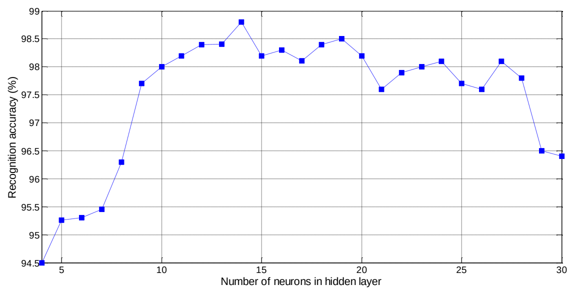

Fig. 14. The effect of number of neurons in hidden layer.

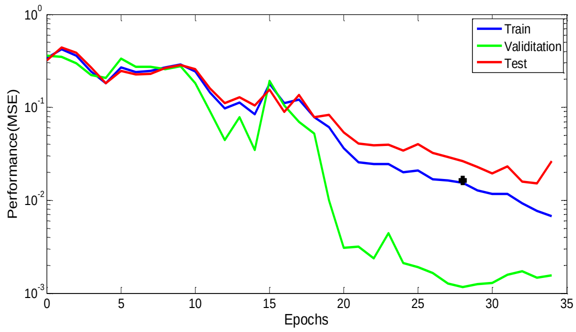

Fig. 15. The training convergence.

Table 4
The control parameters of ICA.

Parameters	Values
Number of countries	50
Number of imperialists	12
γ	0.4
ζ	0.1
β	20
Maximum iteration	50

Table 5
Obtained results after optimization.

Row	Number of layers	Number of neurons			Recognition accuracy (%)
		1st layer	2nd layer	3rd layer	
1	3	28	11	30	99.5
2	**3**	**25**	**15**	**17**	**99.6**
3	3	28	2	28	99.5
4	2	9	11	-	99.4
5	**3**	**8**	**4**	**11**	**99.6**
6	**2**	**8**	**15**	-	**99.6**
7	2	18	7	-	99.5
8	**3**	**9**	**13**	**17**	**99.6**
9	**3**	**8**	**14**	**11**	**99.6**
10	**2**	**20**	**15**	-	**99.6**

References

Abdioglu M, Ozturk K, Gedikli H, Ekici M, and Cansiz A (2015). Levitation and guidance force efficiencies of bulk YBCO for different permanent magnetic guideways. Journal of Alloys and Compounds, 630: 260-265. https://doi.org/10.1016/j.jallcom.2015.01.044

Addeh J, Ebrahimzadeh A, Azarbad M, and Ranaee V (2014). Statistical process control using optimized neural networks: A case study. ISA Transactions, 53(5): 1489-1499. https://doi.org/10.1016/j.isatra.2013.07.018

Bächle T, Hentzelt S, and Graichen K (2013). Nonlinear model predictive control of a magnetic levitation system. Control Engineering Practice, 21(9): 1250-1258. https://doi.org/10.1016/j.conengprac.2013.04.009

Enayatifar R, Sadaei HJ, Abdullah AH, and Gani A (2013). Imperialist competitive algorithm combined with refined high-order weighted fuzzy time series (RHWFTS–ICA) for short term load forecasting. Energy Conversion and Management, 76: 1104-1116. https://doi.org/10.1016/j.enconman.2013.08.039

Hosseini S and Al Khaled A (2014). A survey on the imperialist competitive algorithm metaheuristic: implementation in engineering domain and directions for future research. Applied Soft Computing, 24: 1078-1094. https://doi.org/10.1016/j.asoc.2014.08.024

Li Y, Li J, Zhang G, and Tian WJ (2013). Disturbance decoupled fault diagnosis for sensor fault of maglev suspension system. Journal of Central South University, 20(6): 1545-1551. https://doi.org/10.1007/s11771-013-1646-0

Sun RX, Zheng J, Liao XL, Che T, Gou YF, He DB, and Deng ZG (2014). Thickness dependence of the levitation performance of double-layer high-temperature superconductor bulks above a magnetic rail. Physica C: Superconductivity and its Applications, 505: 80-84. https://doi.org/10.1016/j.physc.2014.07.016

Wen S, Huang T, Zeng Z, Chen Y, and Li P (2015). Circuit design and exponential stabilization of memristive neural networks. Neural Networks, 63: 48-56. https://doi.org/10.1016/j.neunet.2014.10.011

Zhou D, Hansen C, Li J, and Chang W (2010). Review of coupled vibration problems in EMS maglev vehicles. Journal of Acoustics and Vibration, 15(1): 10–23. https://doi.org/10.20855/ijav.2010.15.1255