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Prediction of the Superparamagnetic Limit for Magnetic Storage Medium Using Artificial Neural Networks

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ABSTRACT

In this study, computational techniques based on artificial neural networks for three models were used for training sets, Néel's relaxation time, particle Length and the decay of magnetization were used to perform superparamagnetic calculations for Co_3Pt and FePt typical magnetic storage medium. The magnetic medium's magnetisation stability was studied using the thermal stability coefficient by determining the Néel relaxation time. The superparamagnetic limit was discovered to determine the size of the magnetic particle that can maintain its magnetization for over 10 years, larger particles (8 nm^3 for FePt and 64 nm^3 for Co_3Pt) are required. The decay of magnetization occurs when the thermal stability factor exceeds 40. the effect of changing the neural network's parameters on its performance was examined. The results demonstrated the high sensitivity of the designed neural network's response, which relies on the backpropagation technique to change these parameters.

1. INTRODUCTION

A phenomenon known as superparamagnetism is exhibited by some materials at the nanoscale, especially in the form of nanoparticles, where they exhibit magnetic behavior different from that of conventional magnetism. It is a magnetic property predicted by the scientist Néel in 1949 [1, 2]. Superparamagnetism plays a crucial role in various fields. Superparamagnetism is crucial for preserving information on hard disk drives (HDD), as they use small magnetic regions to represent data. However, excessive superparamagnetism can cause data loss and corruption. Advanced magnetic materials and engineering techniques are used to improve data stability. Magnetic resonance imaging (MRI) relies on superparamagnetic nanoparticles to improve contrast and reveal tissue and structural details. These devices induce magnetic inhomogeneities, making them effective for targeted drug administration and molecular imaging applications [3-6].

In the context of areal density (quantity of data that may be stored in a certain area of a storage medium's surface), the thermal stability factor refers to a magnetic storage media's capacity to retain recorded data in the presence of temperature variations, such as an HDD or magnetic tape [7].

As areal density increases, magnetic grains become smaller, increasing susceptibility to temperature fluctuations, leading to data errors and loss, a crucial factor in high-density storage device design. Techniques like Exchange-Coupled Composite (ECC) Media, grain size control, magnetic anisotropy engineering, thermal barrier layers, and advanced recording techniques can enhance thermal stability in high-density storage media, ensuring modern computing environments meet storage capacity, data reliability, and thermal stability needs [8, 9]. Advanced magnetic storage technologies aim to prevent superparamagnetic effects and ensure data stability, but with growing demand for smaller storage elements and higher densities, researchers are exploring new methods and materials.

Castaldi et al. [10] studied CoPt nanoparticles' properties at -750°, finding a reduction in thickness, formation of L10 phase, and ferromagnetic hardening post-thermal annealing. The magnetic properties range from superparamagnetic to ferromagnetism. The study investigates the growth conditions, nanograin size, and magnetic properties of CoPt nanoparticles on Si substrates. CoPt nanoparticles are advantageous for high-density recording media and exchange bias nanomagnets due to their high anisotropy constant, which prevents superparamagnetic behavior in small particles.

Liedienov et al. [11] examined the critical region of magnetic phase transition for a superparamagnetic particle ensemble in nanopowder.

Khunkitti et al. [12] proposed the use of L10-FePt ECC bit-patterned media in conjunction with microwave-assisted magnetic recording to enhance the writability of magnetic media.

Wang et al. [13] developed a switching type diagram for a FePt/Fe core-shell composite structure using micromagnetic simulation, considering the thickness of the iron shell and the radius of the FePt core. Exchange coupled bit-patterned media are proposed for ultra-high-density magnetic recording storage, overcoming the superparamagnetic size limit. L10 FePt-based thin film nanodot structures are highlighted for their high density, cost-effectiveness, and stability. Composite structures like FePt/Fe with a soft magnetic layer aid in magnetization reversal during writing, enhancing storage density. Traditional

ECC structures face challenges like fabrication complexity, large head keeper spacing, and reliance on exchange-coupling strength. Novel structures like ledge-type isolated nanocomposites and enclosed composite patterned media have been developed to address these issues and improve coercive field reduction.

Artificial intelligence, which focuses on developing technological systems with intelligent behaviour akin to human behaviour, includes artificial neural networks (ANNs). ANNs are a strong tool for data processing and analysis, and they have developed over the past several years into a key element in the field of artificial intelligence in particular [14, 15].

The development of ANNs dates back decades. The development of this fascinating field began with the initial theories and research presented by McCulloch and Walter Pitts in 1943 [16]. Donald Hebb contributed to developing our knowledge of how the brain learns, which became known as the Hebbian Principle [17]. This idea demonstrates how ANNs adjust and improve learning by fortifying connections between neurons when activated simultaneously [18]. Ideas progressed until advanced ANNs emerged in a later period. Frank Rosenblatt developed the "perceptron" in the 1950s, a simpler model of ANNs. In the 1960s, Minsky and Papert's [19]. book "Perceptrons" highlighted the limitations of the perceptron model, demonstrating that perceptron networks cannot solve problems involving nonlinear functions. For a while, this reduced interest in ANNs. In 1986, multi-layer perceptrons, also known as deep ANNs, were discovered, enabling the expression of complex functions through multiple layers and nonlinear functions. Since that time, Artificial ANNs have undergone significant development and are once again a hot topic in the artificial intelligence world. Amazing progress has been made in various applications, including shape recognition, signal analysis, machine translation, and performance enhancement in numerous other engineering and scientific tasks [20].

By performing superparamagnetic limit calculations for Co_3Pt and FePt, known for their high magnetic anisotropy, are used in data storage media to minimize superparamagnetism and enhance reliability. A computational method based on artificial ANNs was developed in this study for use in physical applications.

2. MAGNETIZATION AND SUPERPARAMAGNETISM

The magnetic domains are regions in a material with aligned atomic magnetic moments. When exposed to an external magnetic field, these domains reorient to align with the external field, leading to the overall magnetization of the material. At saturation, the magnetic material has reached its maximum magnetization potential. This means that any additional increase in the external magnetic field will not result in further alignment or strengthening of the atomic magnetic moments within the domain [21].

Easy axes refer to materials' crystalline structure, making certain directions easier for atomic spin alignment due to less energy required. The presence of easy axes can significantly influence the magnetic behaviour and electrical conductivity of a material, making it crucial for various technological applications such as magnetic sensors and data storage devices [22]. Easy axes are commonly observed in materials with anisotropic properties, where the crystal lattice exhibits different physical properties along different directions. In this case, the total internal energy of the domain is as low as possible, anisotropy magnetic occurs when an external magnetic field causes the magnetization vector to rotate away from the easy axis, indicating the internal energy's dependence on the direction of magnetization, and the energy limit for this type is (magnetic anisotropy energy) equal to [23]:

$$E_A = k_u V \tag{1}$$

where, k_u, V is the magnetic particle size distribution and magnetic anisotropy constant respectively. The amount of energy necessary to reverse the direction of magnetization in a magnetic material is referred to as the energy barrier in the field of magnetism. This energy barrier must be broken in order to flip the magnetization direction to align with a different axis when a magnetic domain is fully magnetized along the easy axis.

The material's crystallographic structure, magnetic anisotropy, and interactions between nearby magnetic moments all contribute to the energy barrier [24]. The phenomenon of hysteresis is one of the most basic explanations of ferromagnetism and it occurs due to the alignment of magnetic domains within the material. The reversible component of magnetization refers to the changes that can be easily reversed by changing the external magnetic field, while the non-reversible component represents the residual magnetization that remains even after removing the external field because some parts of the magnetic sample cross the energy barrier. The energy barrier equals the anisotropic energy in the absence of an external magnetic field.

The magnetic anisotropic energy barrier decreases at a certain temperature and when the size of the magnetic particle is small, which causes the magnetic particle to rotate its magnetization vector and overcome the thermal energy. Compared to paramagnetism, susceptibility is much higher. Superparamagnetic materials, in contrast to ferromagnetic and ferrimagnetic materials, change from their ferromagnetic and ferrimagnetic states to their paramagnetic states at temperatures lower than the Curie temperature [6].

Two magnetization states are created by the anisotropic energy and are separated by an energy barrier. The following Arrhenius equation can be used to calculate the probability that the magnetization will reverse at a specific temperature [25]:

$$f = f_o \exp(-T_{SF}) \tag{2}$$

$$T_{SF} = E_B / K_B T \tag{3}$$

where, f_o, T_{SF}, k_B, T are the frequency of attempting to cross the energy barrier, thermal stability factor, Boltzmann constant and temperature. In order to retain one bit of stored information in a particle for time > 10 years (3×10^8 s), then $f < 3.33 \times 10^{-9}$ Hz [3]. The Néel relaxation time is the time rate between two flips for a particle's magnetization to randomly reverse as a result of thermal fluctuations, which is determined by the Néel-Arrhenius equation given below [26]:

$$\tau_N = \tau_o \exp(T_{SF}) \tag{4}$$

where, the time of attempting is a property of the material.

When evaluating the superparamagnetic limit, it's crucial to consider the thermal decay of grain magnetization due to opposing fields. This can decrease the overall magnetization of the media, impacting its superparamagnetic behaviour. Therefore, analyzing grain thermal stability and susceptibility to opposing fields is essential.

Consider an arrays of small particles, the probability of the magnetization not having $P(t)=\exp(-t/\tau_N)$ and having (1- P(t)) hopped the energy barrier, M_o It represents the initial saturated magnetization and M_f represents the final saturated magnetization, where $M_f = -M_o$ at opposing field. The decay of the magnetization due to the superparamagnetic phenomenon can be written as follows [3]:

$$M(t) = 2M_o[P(t) - 1/2] \tag{5}$$

3. HUMAN BRAIN AND ARTIFICIAL NEURAL NETWORKS

The human brain, composed of about billion neurons connected by neural connections, is responsible for human efficiency in tasks like language understanding, decision making, and problem-solving. The number of neurons increases or decreases with age, and the brain weighs about 1.5 kilograms and consumes 20% of the body's energy [27].

A nerve cell consists of three sections: cell body or soma contains the nucleus, dendrites connect neighbouring cells, and axons transmit electrical signals to other neurons, muscles, or glands, carrying information for sensory perception, motor control, and memory, contributing to the complex network of communication within the brain [28].

ANNs are computational models inspired by human brains. They are composed of interconnected nodes arranged in layers. These ANNs are used in machine learning for tasks like pattern recognition, classification, and regression. The architecture of ANNs consists of neurons that receive inputs (input layer), perform a weighted sum, apply an activation function (hidden layer) and generate outputs (output layer). The training process for ANNs includes forward propagation, which computes the final output, backward propagation, which modifies the network's weights and biases based on the difference between projected and actual outputs, and assessing a model's performance by comparing predicted outputs to actual targets using the loss function and to minimize it using optimizer [29].

4. LEARNING ALGORITHMS OF ARTIFICIAL NEURAL NETWORKS

Supervised learning is a technique for training an ANN model with labeled data that employs techniques such as backpropagation, stochastic gradient descent, momentum, learning rate scheduling, and adaptive learning rates. These methods aid in minimizing loss, updating weights incrementally, and optimizing the model's convergence. They also support dynamic adjustment of learning rates based on model performance. Unsupervised learning is a method for training networks using unlabeled data to identify patterns or structures. It uses many algorithms such as K-means to group similar data points, reduce dimensionality, and generate new data samples [30]. ANNs can predict thermal stability, superparamagnetism, and magnetic anisotropy in materials. They can model material responses to temperature changes, predict superparamagnetic behavior, and capture directional anisotropy dependence for various applications.

5. NEURAL NETWORKS LEARNING RULES

ANNs learn by rules or algorithms. These rules dictate how the network updates its parameters to minimize the difference between predicted outputs and actual target values. Common learning rules include Hebbian Learning, Perceptron Learning Rule, Delta Rule, Backpropagation, Competitive Learning, Hopfield Network Learning Rule, Kohonen Self-Organizing Map Learning Rule, and Adaptive Resonance Theory (ART). Hebbian Learning strengthens connections between neurons if they are active simultaneously, while Perceptron Learning adjusts weights based on actual and predicted outputs. Competitive Learning competes for active neurons to adjust weights sensitivity to input patterns. The choice of learning rule depends on network architecture, task, and data characteristics [31].

6. RESULTS AND DISCUSSION

Figure 1 shows the comparison between the predicted and original value of Néel's relaxation time for different values of (Eq. 4) which plays a critical role in determining the stability of the magnetization state in a magnetic medium and its potential impact on information storage where is smaller it is, the greater the possibility of magnetization reversal and thus the loss of information stored in the magnetic medium. A higher thermal stability factor indicates a more stable magnetization state, as seen by the longer relaxation times. A thermal stability factor of over 40 indicates a magnetic medium's ability to preserve stored information for over ten years. This is crucial for data storage applications, ensuring reliable retention over long periods. A higher factor indicates less susceptibility to random changes from thermal fluctuations.

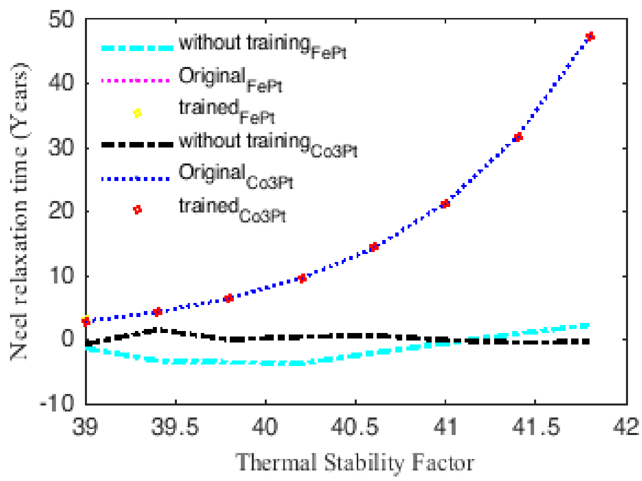


Figure 1. Néel's relaxation time V.s the thermal stability factor

The results were calculated with an anisotropy constant k_u and saturation magnetization M_s as shown in Table 1 at room temperature, (k_B=1.38 × 10^{-16} erg/Kelvin) Boltzmann constant, and an attempt time (τ_o=10^{-9} s).

Table 1. Magnetic properties of materials.

	Co_3Pt	FePt
$K_u \times 10^6$ erg/cm^3	2	7
M_u emu/cm^3	1100	1400

Figure 2 shows the comparison between the original and predicted value of particle Length for different values of the thermal stability factor T_{SF} (Eq. 3), this figure shows that a cubic-shaped magnetic nanoparticle with a single domain needs to be larger than 2 nm and 4 nm in all dimensions for FePt and Co_3Pt. This means that obtaining information stored in this medium for more than 10 years requires a particle size larger than 8 nm^3 for FePt and 64 nm^3 for Co_3Pt. When the thermal stability factor exceeds 40, this takes place.

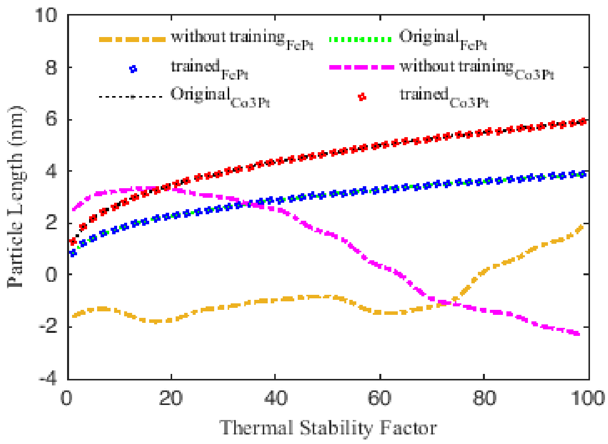


Figure 2. Particle Length V.s the thermal stability factor

Figure 3 shows the comparison between the original and predicted value of the decay of magnetization as a function of time (Eq. 5) from spontaneous magnetization 1140 to 400 and from 1110 to 430 for a magnetic storage medium with a size of 8 nm^3 and 64 nm^3 for FePt and Co_3Pt respectively.

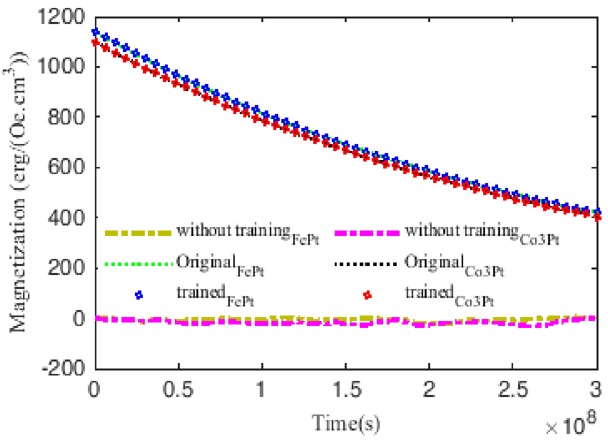


Figure 3. The decay of magnetization as a function of time

The results underscore the importance of particle size in ensuring the thermal stability of magnetic storage media. FePt and Co_3Pt are still suitable materials for high-density storage, but they will only be useful in the long run if their particle sizes stay within a certain limit. Key to the advancement of magnetic storage technology is balancing thermal stability and storage density, improving material properties, and using creative fabrication methods. Because of these factors, magnetic storage will continue to be a pillar of information technology, ensuring dependable, long-term data preservation.

The effect of changing ANNs parameters on its performance was studied. The results show the extreme sensitivity of the response of the designed ANNs to these parameters. We obtained a close match for the results using the ANNs architecture, a feedforward ANNs was utilized One neuron was present in the input layer network. in addition to 10 neurons in the hidden layer of the sigmoid transfer function, three neurons that linear transfer function inside the layer of output. We all Levenberg-Marquardt algorithm was utilized for Instruction. The parameter specifies the maximum number of training epochs, which are complete passes through the entire training dataset, in this case, 100 epochs. The momentum constant, with a high value of 0.9, accelerates convergence by introducing a fraction of the previous weight update into the current update. When the input signal propagates to the appearance of unknown signs, each of these signals generates the appropriate product and message in the form of a single signal to several neurons simultaneously.

In ANNs, the mean square error MSE is commonly used as a loss function, especially in regression tasks. The loss function evaluates the degree to which the predictions of a neural network accurately match the actual data. The objective of training a ANNs are to minimize the loss function. Figure 4 represents variations in the MSE versus the epochs. The graph indicates that at epoch 80, 51, the best training performance of 9.7808×10^{-6}, 9.9762×10^{-6} was recorded for Co_3Pt and FePt respectively for particle length model. As a result, there is little final mean square error, it means that particle length model is performing well on the training sets.

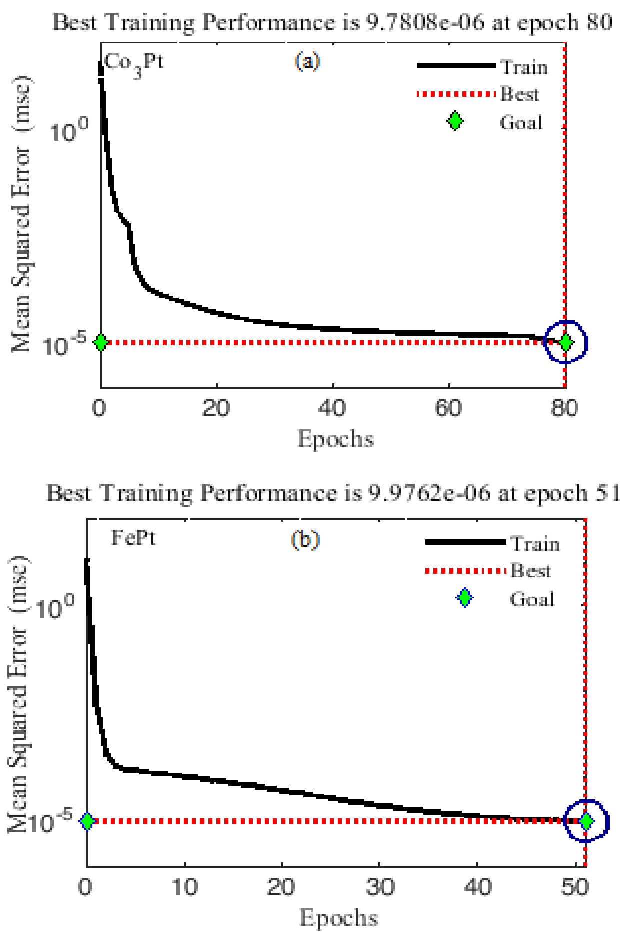
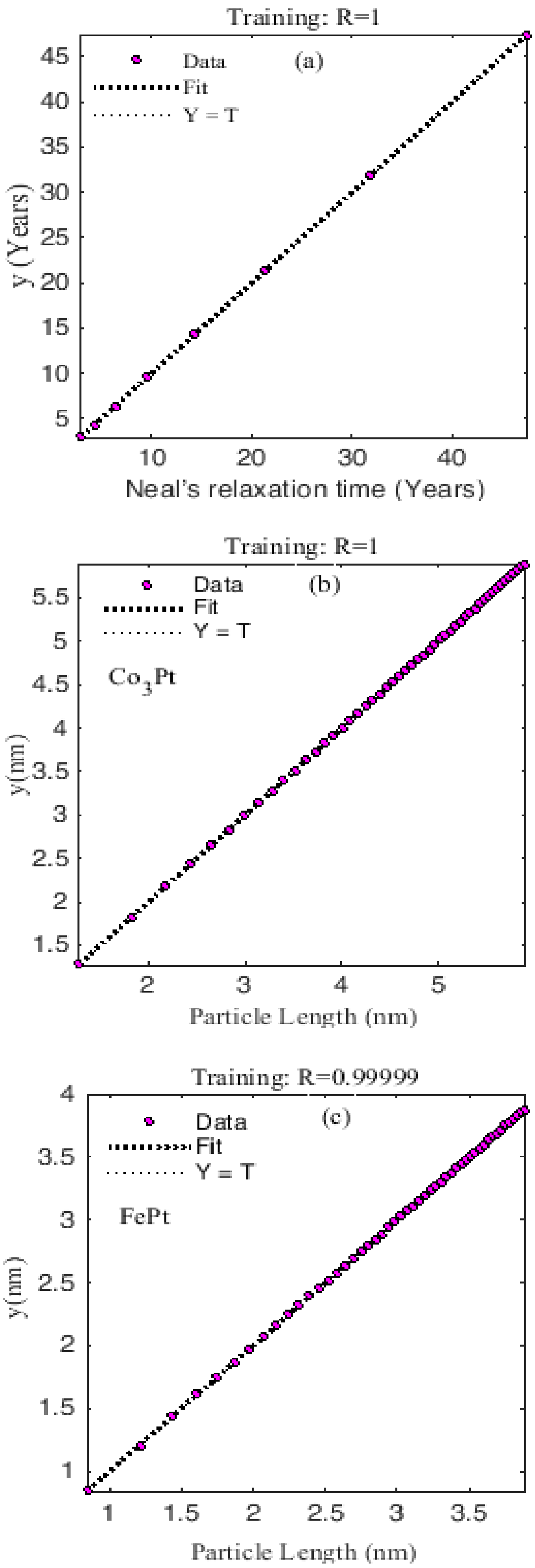


Figure 4. Performance goal of ANNs for a) Co_3Pt, b) FePt

The correlation coefficient *R* between the original and anticipated values was calculated using linear regression as shown in Figure 5. The plots show *R* for Néel's relaxation time, Particle Length and magnetization decay in Figures 5a, 5b, 5c, 5d and 5e for Co_3Pt and FePt respectively, from this figure, both for training and testing data, the output closely follows the targets. This shows that the model has good generalization capabilities to new data and can accurately predict desired outcomes. It also indicates that the model is learning well and improving over time because the output consistently converges towards the targets.



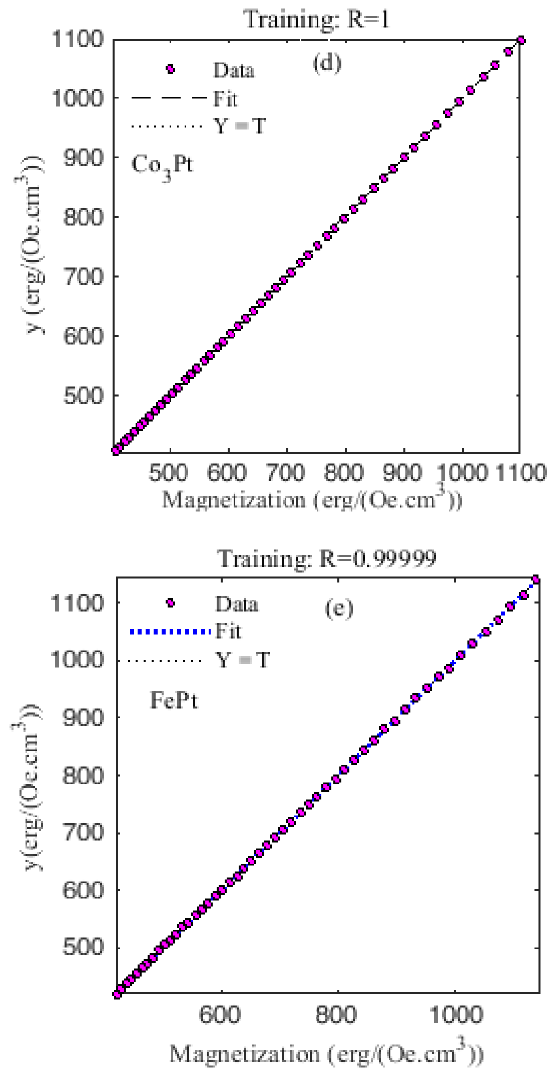


Figure 5. Linear regression for training and testing data

R is not the only piece of information that can be obtained from linear regression analysis. It also provides the linear relationship's equation, which usually takes the form y = mx + b, represents the relationship between y (dependent variable) and x (independent variable) and the slope of the regression line (m). This equation allows us to predict the value of y based on the target value x as shown in the Table 2. Furthermore, linear regression analysis can also provide insights into the statistical significance of the relationship between the variables, helping determine if the observed relationship is likely to occur by chance or if it is statistically significant.

Table 2. Linear relationship's equation parameters

	Co_3Pt		**FePt**	
Models	**m**	**b**	**m**	**b**
Néel's relaxation time	1	36×10^{-5}	1	13×10^{-4}
Particle Length	1	11×10^{-4}	1	64×10^{-5}
Magnetization decay	1	3.1×10^{-7}	1	54×10^{-2}

7. CONCLUSIONS

Thermal stability factor determines magnetization state stability and impact on information storage. Smaller factors increase magnetization reversal and loss of stored information. A higher factor indicates more stable magnetization, while over 40 indicates long-term information preservation. A higher factor reduces susceptibility to thermal fluctuations. Particles with a higher thermal stability factor respond to applied fields based on their switching characteristics, acquiring stable magnetization quickly.

Obtaining information stored in a storage medium for more than 10 years requires a particle size larger than 8 nm^3 for FePt and 64 nm^3 for Co_3Pt.

A magnetic storage medium with a size of 8 nm^3 and 64 nm^3 for FePt and Co_3Pt, respectively, showed a decay in magnetization as a function of time from spontaneous magnetization from 1140 to 400 and from 1110 to 430.

A feedforward ANNs were used, with one neuron in the input layer, 10 neurons in the hidden layer, and three linear functions in the output layer. The Levenberg-Marquardt algorithm was used for instruction, and a high momentum constant accelerates convergence.

In this study, ANNs are highly relevant due to their ability to model the intricate relationships between the physical properties of materials and their magnetic behaviors. By training the network on experimental data, the ANN can learn to predict outcomes based on input parameters with high accuracy, even when dealing with the non-linear and multi-dimensional nature of the problem.

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NOMENCLATURE

f_o	frequency of attempting to cross the energy barrier, s^{-1}
τ_o	attempt time, s
k_B	Boltzmann constant , erg/Kelvin
k_u	anisotropy constant, erg/cm
M_s	saturation magnetization, emu/cm^3

Subscripts

B	Boltzmann
u	anisotropy
s	saturation