Article

Extreme Learning Machine Approach to Modeling the Superconducting Critical Temperature of Doped MgB₂ Superconductor

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Abstract: Magnesium diboride (MgB₂) superconductor combines many unique features such as transparency of its grain boundaries to super-current flow, large coherence length, absence of weak links and small anisotropy. Doping is one of the mechanisms for enhancing these features, as well as the superconducting critical temperature, of the compound. During the process of doping, the MgB₂ superconductor structural lattice is often distorted while the room temperature resistivity, as well as residual resistivity ratio, contributes to the impurity scattering in the lattice of doped samples. This work develops three extreme learning machine (ELM)-based empirical models for determining MgB₂ superconducting critical temperature (T_C) using structural distortion as contained in lattice parameters (LP) of doped superconductor, room temperature resistivity (RTR) and residual resistivity ratio (RRR) as descriptors. The developed models are compared with nine different existing models in the literature using different performance metrics and show superior performance over the existing models. The developed SINE-ELM-RTR model performs better than Intikhab et al. (2021)_linear model, Intikhab et al. (2021)_Exponential model, Intikhab et al. (2021)_Quadratic model, HGA-SVR-RRR(2021) model and HGA-SVR-CLD(2021) model with a performance improvement of 32.67%, 29.56%, 20.04%, 8.82% and 13.51%, respectively, on the basis of the coefficient of correlation. The established empirical relationships in this contribution will be of immense significance for quick estimation of the influence of dopants on superconducting transition temperature of MgB₂ superconductor without the need for sophisticated equipment while preserving the experimental precision.

Keywords: room temperature resistivity; lattice parameters; extreme learning machine; superconducting critical temperature; residual resistivity ratio; MgB₂ superconductor

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1. Introduction

Discovery of superconductivity behavior in magnesium diboride (MgB₂) widened the potentials of the material for superconductor applications, such as liquid-helium-free magnetic resonance imaging systems, generators, transformers and fault current limiters, among others [1–4]. Apart from the fact that MgB₂ is a compound made from two relatively cheap, light elements, the abundance of these elements is another significant factor that enhances its fabrication at a very low cost [5]. Other unique features of this compound include transparency of its grain boundaries to super-current flow, large coherence length, absence of weak links and small anisotropy [6,7]. These unique features make MgB₂ superconductor admirable, despite its lower superconducting transition temperature (T_C), compared to many conventional high-temperature superconductors. MgB₂ is a two-band, intermetallic superconductor characterized by a simple, hexagonal crystal lattice structure. Weakness in the inter-band electron–phonon interaction, as a result of doping, suppresses its superconducting transition temperature [8,9]. Among the mechanisms for altering

the superconducting properties of MgB_2 superconductor is influencing the E_{2g} phonon frequency, as well as the density of state, through the introduction of foreign materials into the crystal lattice structure of the parent MgB_2 compound, which, consequently, results in lattice distortion [8]. Among the aims of this research is the establishment of a relationship between lattice distortion and MgB_2 superconducting critical temperature using extreme learning machine computational methods so as to enhance quick characterization of MgB_2 superconductor without the need for costly cryogenic devices.

Apart from lattice distortion, incorporation of foreign materials into MgB_2 superconductor by doping introduces disorder, as well as lattice impurity scattering, which becomes manifested through electrical resistivity enhancement [10]. Resistivity is also affected by the defects present inside the grains, while the value is altered when foreign material, such as carbon, is substituted into atomic sites containing boron atoms [11]. Concentration of dopants significantly affects the value of resistivity residual ratio since lattice distortion created by dopants enhances the impurity scattering [12]. The electrical resistivity is strongly correlated with extrinsic factors, such as inclusions, inter-grains, defects, voids, porosity and polycrystalline anisotropy, among others [13]. The electron scattering due to phonon contribution, as well as intra-granular defects, decreases as the superconducting critical temperature is approached. Hence, intra-granular defects due to dopants incorporation significantly contribute to the resistivity of MgB_2 superconductor close to the critical temperature [14]. Similarly, the sample crystallinity and the extent of MgB_2 inter-grain connectivity are reflected by the values of room temperature resistivity (RTR) and resistivity residual ratio (RRR) [15]. The lattice parameter reduction, as well as the impurity scattering due to the incorporated dopants, influences superconducting bonds in MgB_2 superconductor since the mean free path becomes shortened and, ultimately, leads to a decrease in the coherence length [11]. The employed methodology in this work physically relates the descriptors with the superconducting critical temperature while the nature of the relationship is established using extreme learning machine [16]. Therefore, the extreme learning machine (ELM) algorithm is employed in this present work to develop SINE-ELM-RTR and SIG-ELM-RRR models that, respectively, determine the critical temperature of doped MgB_2 superconductor using RTR and RRR as descriptors. In order to factor in distortion due to the incorporated dopants, this work also develops a SINE-ELM-LP model for estimating superconducting critical temperature using the lattice parameter (LP) as a descriptor.

Extreme learning machine is an extension of a single-layer, feed-forward neural network with characteristic randomization of the bias of hidden layer, as well as the input weights [17]. This uniqueness of the ELM algorithm translates to fast computational speed and less complexity with minimum training error [18,19]. Another interesting merit of a computational-intelligence-based extreme learning machine is the random generation of the hidden layer threshold, as well as the input layer weights, in contradistinction to the classical, feed-forward neural networks that mostly employ the ladder descent method for their training process. These features significantly promote and widen the application of the ELM algorithm in many fields of applications [20–24]. The influence of noise insertion on machine learning techniques has been treated elsewhere [25]. A stochastic-based model with multiplicative white Gaussian noise inclusion was developed to obtain cell concentration spatial distribution for two investigated picophytoplankton groups while the proposed theoretical profile reproduced the real distribution [26]. Similarly, phase-type distribution has been proposed elsewhere to study statistical distribution of switching voltages instead of the well-explored Weibull distribution [27]. A novel and interesting approach on the basis of the Uhlmann curvature has been applied to investigate non-equilibrium, steady-state quantum phase transition with emphasis on the role of quantum, as well as classical, fluctuations [28]. Cultivation and spatial ordering for the dissociated hippocampal network were further studied to exemplify a brain-on-chip system for new-generation robotic application [29]. This work considers an ordinary extreme-learning-machine-based model due to insignificant influence of fluctuation and noise on the employed experimental data for simulation. The ELM-based model developed in this contribution outperforms existing

models in the literature due to intrinsic properties of the algorithm that approximate pattern and functions connecting descriptors and the target with minimum possible error.

The remaining part of the manuscript is arranged as follows: Section 2 describes the mathematical background of extreme learning machine. Computational methodologies, as well as a description of the dataset, are all included in Section 2 of the manuscript. Section 3 presents and discusses the results. The estimates of the present and existing models are compared in Section 3, while Section 4 concludes the manuscript.

2. Mathematical Background and Computational Methodology

The mathematical formulation of extreme learning machine is briefly described in this section. The acquisition and description of the physical details of the implemented dataset are also presented. The section further presents the computational strategies employed in the model development.

2.1. Mathematical Description of the Extreme Learning Machine Algorithm

Extreme learning machine is a feed-forward neural network with reduced complexity and a single hidden layer [17]. The algorithm is capable of approximating continuous function that is complex and, ultimately, leads to exceptional learning outcomes. Apart from the complexity characterizing the traditional, feed-forward neural network, adjusting the network parameters while training the algorithm contributes significantly to the computational time intensiveness of the network. The proposed extreme learning algorithm circumvents these aforementioned disadvantages of ordinary, single-hidden-layer, feed-forward neural networks [22,30,31]. A training set of distortions (D), as contained in the lattice parameters (L) of doped MgB₂ superconductors, and the corresponding transition temperature (T) at superconducting phase were considered as $\sigma = (D_k, T_k)$, $k = 1, 2, 3, \dots, M$, where M is the number of doped samples investigated, and $D_k = \{L_{k1}, L_{k2}, \dots, L_{kN}\}^T \in \mathcal{R}^N$ is the input vector, while $T_k = \{T_{k1}, T_{k2}, \dots, T_{kp}\}^T \in \mathcal{R}^P$ is the output vector. The approximated mathematical model generated by the SINE-ELM-LP model is presented in Equation (1):

$$T_k = \sum_{i=1}^{\zeta} \beta_i f(\varnothing_i \cdot D_k + b_i) \quad (1)$$

where ζ and β_i , respectively, stand for the number of hidden nodes, and the weight corresponds to the i th hidden node. The weight vector joining the hidden layer with the lattice parameters is referred to as an input layer node represented as $\varnothing_i = [\varnothing_{i1}, \varnothing_{i2}, \dots, \varnothing_{ip}]^T$. The activation function and the hidden layer neuron offset are denoted by f and b_i , respectively. The matrix representation of the estimated transition temperature (T^{estim}) is computed in accordance with Equation (2):

$$T^{\text{estim}} = H\beta = \begin{bmatrix} f(\varnothing_1 \cdot D_1 + b_1) & \cdots & f(\varnothing_{\zeta} \cdot D_1 + b_{\zeta}) \\ \vdots & \cdots & \vdots \\ f(\varnothing_1 \cdot D_M + b_1) & \cdots & f(\varnothing_{\zeta} \cdot D_M + b_{\zeta}) \end{bmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_{\zeta} \end{bmatrix} \quad (2)$$

The output matrix of the hidden layer is symbolized as H, while the weights connecting the output layer with the hidden layer are represented as $\beta = [\beta_1, \beta_2, \dots, \beta_{\zeta}]^T$. The activation function includes polynomial, linear, sigmoid and sine function, among others. The offset for the hidden layer, as well as the input weights, is fixed during the training, while determining the least-square solution to Equation (3) remains the prime objective of the algorithm.

$$\text{Min} | H\beta - T^{\text{estim}*} | \quad (3)$$

Equation (4) presents the solution to Equation (3) where H^* represents the Moore–Penrose generalized inverse of H :

$$\hat{\beta} = H^*Y \quad (4)$$

The development of the SINE-ELM-RTR and SIG-ELM-RRR models followed similar mathematical formulation to the SINE-ELM-LP model except that RTR and RRR, respectively, served as descriptors for the SINE-ELM-RTR and SIG-ELM-RRR models, while SINE and SIG in the model nomenclature indicated the activation function.

2.2. Physical Description of the Dataset

The measured superconducting critical temperature, room temperature resistivity (RTR), crystal lattice parameters (LP) of doped MgB_2 superconductor and residual resistivity ratio (RRR) employed in developing the SINE-ELM-RTR model, SINE-ELM-LP model and SIG-ELM-RRR model were obtained from the literature [1–3,10–13,15,32–52]. While the presence of dopants in MgB_2 superconductor results in distortion, with which the developed SINE-ELM-LP model estimates the superconducting critical temperature, RTR and RRR measure the degree of disorder and impurity scattering resulting from the introduced dopants. Hence, the choice of RTR and RRR as descriptors for the SINE-ELM-RTR and SIG-ELM-RTR model becomes necessary for effective determination of the influence of dopants on superconducting critical temperature. Development of the SINE-ELM-LP model employed one hundred and sixty-two MgB_2 superconductors with incorporated foreign materials prepared under various experimental conditions. Distortions along the a-axis and c-axis of the crystal structure of doped MgB_2 superconductor served as the descriptors of the SINE-ELM-LP model. Twenty-four compounds of MgB_2 superconductor samples with incorporated dopants were utilized in developing the SINE-ELM-RTR model while the room-temperature resistivity of the prepared samples served as the descriptor for this model. In the case of the developed SIG-ELM-RRR model with the residual resistivity ratio as the input, fifty-one doped samples of MgB_2 superconductor were implemented for model development.

2.3. Computational Methodology

Development of ELM-based models was computationally carried out using the computing part of MATLAB. The data points extracted from doped samples of MgB_2 superconductors were randomized for data points uniform distribution enhancement and, subsequently, separated into training and testing sets with an 8:2 ratio in the case of the SINE-ELM-LP and SIG-ELM-RRR model, while the partitioning ratio of 9:1 was adopted for the SINE-ELM-RTR model. Randomization becomes paramount in model effectiveness enhancement since it prevents a situation in which the model is subjected to testing procedures on a pattern it has not acquired and, subsequently, over-fitted. The following steps are the computational strategies of the developed ELM algorithm. It should be noted that similar computational strategies were adopted for each of the three developed models except that RRR was the descriptor for the SIG-ELM-RRR model with sigmoid activation function, and RTR served as the descriptor for the SINE-ELM-RTR model with sine activation function, while the SINE-ELM-LP employed lattice parameters as descriptors with sine activation function.

Step I: Randomization of hidden layer offset and input layer: The offset of the hidden layer b_i , as well as the input weights, were generated randomly through the MATLAB pseudo-random number generator using a seeding approach.

Step II: Computation of output matrix H after activation function selection. Activation function was selected from sine, sigmoid (Sig) and tribas, among others.

Step III: Computation of $\hat{\beta}$ weights, joining the output layer with the hidden layer using the training set of data.

Step IV: Prediction and generalization strength evaluation. Using the testing dataset coupled with the determined output matrix in Step III, the developed ELM-based model

was evaluated using the root mean square error (RMSE), mean square error (MSE) and correlation coefficient (CC).

Step V: Step I to Step IV were repeated with different activation functions and the best model parameters in every iteration were saved for future implementation.

The computational flow chart explaining the step-by-step procedures of the employed computational strategies and procedures is presented in Figure 1.

Figure 1. Flow chart explaining the computational description of ELM-based models.

3. Results and Discussion

The estimates of ELM-based models are contained in this section. Empirical relations that facilitate easy implementation of the developed ELM-based models are further presented. Comparison of the estimates of the developed models with nine different models existing in the literature is also presented.

3.1. ELM-Generated Empirical Relation for Determining Superconducting Critical Temperature of MgB_2 Superconductors

Among the merits of an ELM-based model in comparison with other computational intelligence methods is the generation of easily implementable empirical equations. The empirical equation for each of the developed models is presented in Equations (5)–(7);

Equation (5) for the developed SINE-ELM-LP model, Equation (6) for SINE-ELM-RTR model and Equation (7) for the SIG-ELM-RRR model, respectively.

$$\text{SINE} - \text{ELM} - \text{LP} = \sum_{j=1}^p \beta_j \text{Sine}(\phi_j \cdot \text{LP}_s + b_j) \quad (5)$$

$$\text{SINE} - \text{ELM} - \text{RTR} = \sum_{t=1}^z \beta_t \text{Sine}(\phi_t \cdot \text{RTR}_t + b_t) \quad (6)$$

$$\text{SIG} - \text{ELM} - \text{RRR} = \sum_{n=1}^N \beta_n \text{Sigmoid}(\phi_n \cdot \text{RRR}_x + b_n) \quad (7)$$

where p , z and N , respectively, represent the number of doped MgB_2 superconducting samples available for simulation. The numbers of hidden nodes for the developed SINE-ELM-LP, SINE-ELM-RTR and SIG-ELM-RRR models are represented as j , t and n , respectively, where $j = 68$, $t = 40$ and $n = 28$ are the optimum values. The weights (β_j , β_t and β_n) correspond to each of the nodes, as well as the biases (b_j , b_t and b_n), and are presented in the Appendix A to facilitate reproducibility of the results presented.

3.2. Comparison of Performance of the Developed ELM-Based Models

The future prediction and generalization strength of the developed ELM-based models were compared using performance metrics such as the mean squared error (MSE), correlation coefficient (CC) and root mean square error (RMSE). Figure 2 presents the comparison using a testing set of data. The comparison presented in Figure 2a on the basis of RMSE shows that the developed SINE-ELM-RTR model outperformed the SIG-ELM-RRR and SINE-ELM-LP models with a performance improvement of 68.78% and 62.60%, respectively, while the developed SINE-ELM-LP model performed better than the SIG-ELM-RRR model with an improvement of 16.51%.

Figure 2. Testing performance comparison of the developed ELM-based models. (a) comparison on the basis of root mean square error (b) comparison on the basis of correlation coefficient (c) comparison on the basis of mean squared error.

With the coefficient of correlation as a performance evaluation parameter, as presented in Figure 2b, the developed SINE-ELM-RTR model performed better than the SIG-ELM-RRR and SINE-ELM-LP model with a performance improvement of 40.69% and 28.18%, respectively. Using the same parameter, the developed SINE-ELM-LP model outperformed the SIG-ELM-RRR model with a performance enhancement of 17.41%. With the mean square error metrics presented in Figure 2c, the developed SINE-ELM-RTR model showed better performance compared with the SIG-ELM-RRR and SINE-ELM-LP models with respective performance improvements of 90.25% and 86.01%, while the developed SINE-ELM-LP model demonstrated better performance with a 30.30% improvement compared with the SIG-ELM-RRR model.

The correlation cross-plot for the developed models is presented in Figure 3. The superiority of the developed SINE-ELM-RTR model over the other two models is manifested through alignment of its data points as compared to the others. The performances of each of the developed ELM-based models at the testing phase of model development are presented in Table 1.

Figure 3. Correlation cross-plot for the developed ELM-based model.

Table 1. Performance measuring parameters and their values for the developed models evaluated on testing dataset.

	MAE	% Improvement of SINE-ELM-RTR	% Improvement of SINE-ELM-LP	% Improvement of SIG-ELM-RRR
Intikhab et al. (2021)_linear [53]	3.1764	99.0606	76.97842	69.6459
Intikhab et al. (2021)_Exponential [53]	2.709	98.89851	73.00637	64.40872
Intikhab et al. (2021)_Quadratic [53]	2.0817	98.56659	64.87211	53.68364
HGA-SVR-RTR (2021) [54]	0.0704	57.61471		
HGA-SVR-RRR (2021) [54]	0.2463	87.885		
HGA-SVR-CLD (2021) [54]	0.6097	95.10591		
GRP-prediction (2020) [55]	0.28	89.34313		
STTE (2016) [56]	0.279	89.30493		
STTE (2014) [6]	1.00	97.01608	26.87427	3.583232
SIG-ELM-RRR (this work)	0.964168	96.90518	24.15662	
SINE-ELM-LP (this work)	0.731257	95.91946		
SINE-ELM-RTR (this work)	0.029839			

3.3. Performance Superiority of the Developed ELM-Based Models over Nine Existing Models in the Literature

The performance of the developed SINE-ELM-RTR model was compared on the basis of mean absolute error (MAE) with nine different existing models in the literature. The comparison was made using the entire dataset purposely to ensure just comparison. The developed SINE-ELM-LP and SIG-ELM-RRR model were also compared with five different existing models.

The developed SINE-ELM-RTR model outperformed Intikhab et al.'s 2021 linear model [53], Intikhab et al.'s 2021 exponential model [53] and Intikhab et al.'s 2021 quadratic model [53], with a performance improvement of 99.06%, 98.89% and 98.57%, respectively,

using MAE as a performance metric, as presented in Figure 4a. A performance superiority of 57.61%, 87.89% and 95.11% was respectively obtained, as presented in Figure 4b, while comparing the performance of the developed SINE-ELM-RTR model with the existing HGA-SVR-RTR (2021) [54], HGA-SVR-RRR (2021) [54] and HGA-SVR-CLD (2021) [54] models using the same performance evaluation parameter. The developed SINE-ELM-RTR model further outperformed the existing GRP-prediction (2020) [55] model, STTE (2016) model [56] and STTE (2014) [6] model with a performance enhancement of 89.34%, 89.30% and 97.02%, respectively, as shown in Figure 4c.

Figure 4. Comparison between the performance of developed SINE-ELM-RTR model and the existing models on the basis of mean absolute error (a) comparison of the developed model with Intikhab et al. (2021)_linear [53], Intikhab et al. (2021)_Exponential [53] and Intikhab et al. (2021)_Quadratic [53] (b) comparison of the developed model with STTE(2016) [56], GRP-Prediction (2020) [55] and STTE(2014) [6] (c) comparison of the developed model with HGA-SVR-RTR(2021) [54], HGA-SVR-RRR(2021) [54] and HGA-SVR-CLD(2021) [54].

Similarly, the developed SINE-ELM-RTR model also performed better than the developed SIG-ELM-RRR and SINE-ELM-LP model with a performance enhancement of 96.91% and 95.92%, respectively. While comparing the performance of the developed

SINE-ELM-LP model with existing models in the literature, performance improvements of 76.98%, 73.01%, 64.87% and 26.87% were obtained over the existing Intikhab et al. 2021 linear model [53], Intikhab et al. 2021 exponential model [53], Intikhab et al. 2021 quadratic model [53] and STTE (2014) model [6], respectively, as depicted in Figure 5a. A performance comparison of the developed SIG-ELM-RRR model with existing models on the basis of the MAE metric is presented in Figure 5b. The developed SIG-ELM-RRR model performed better than the existing Intikhab et al. 2021 linear model [53], Intikhab et al. 2021 exponential model [53], Intikhab et al. 2021 quadratic model [53] and STTE (2014) model [6], with an improvement of 69.65%, 64.41%, 53.68% and 3.58%, respectively. Table 2 presents the performance of each of the developed models on the basis of MAE and the comparison with other existing models. Percentage improvements of each of the developed models over the existing models are also presented in the table.

Figure 5. Comparison between the performance of developed SINE-ELM-LP and SIG-ELM-RRR models and the existing models on the basis of mean absolute error (a) comparison of the developed SINE-ELM-LP model with STTE(2014) [6], Intikhab et al. (2021)_Quadratic [53], Intikhab et al. (2021)_Exponential [53] and Intikhab et al. (2021)_linear [53] (b) comparison of the developed SIG-ELM-RRR model with STTE(2014) [6], Intikhab et al. (2021)_Quadratic [53], Intikhab et al. (2021)_Exponential [53] and Intikhab et al. (2021)_linear [53].

3.4. Investigating the Impurity Scattering Potential of Carbon-Encapsulated Amorphous Boron for MgB₂ Superconducting Critical Temperature Enhancement Using Developed SINE-ELM-RTR Model

The superconducting-critical-temperature-enhancement tendency of carbon was investigated using the developed SINE-ELM-RTR model through carbon-encapsulated amorphous boron. The comparison of the results of the developed SINE-ELM-RTR model with measured values [10] is presented in Figure 6. The observed enhancement of superconducting properties due to the carbon incorporation in the lattice structure of MgB₂

superconductor can be attributed to the homogenous distribution of carbon particles in the doped sample as a result of the implemented encapsulation. This leads to the grain of reacted MgB_2 being restricted from unnecessary growth [10]. The observed increase in resistivity due to impurity scattering in the lattice of MgB_2 served as the descriptor for the developed model.

Table 2. Performance comparison of the developed model with existing models.

	MAE	% Improvement of SINE-ELM-RTR	% Improvement of SINE-ELM-LP	% Improvement of SIG-ELM-RRR
Intikhab et al. (2021)_linear [53]	3.1764	99.0606	76.97842	69.6459
Intikhab et al. (2021)_Exponential [53]	2.709	98.89851	73.00637	64.40872
Intikhab et al. (2021)_Quadratic [53]	2.0817	98.56659	64.87211	53.68364
HGA-SVR-RTR (2021) [54]	0.0704	57.61471		
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STTE (2016) [56]	0.279	89.30493		
STTE (2014) [6]	1.00	97.01608	26.87427	3.583232
SIG-ELM-RRR (this work)	0.964168	96.90518	24.15662	
SINE-ELM-LP (this work)	0.731257	95.91946		
SINE-ELM-RTR (this work)	0.029839

Figure 6. Influence of carbon incorporation on superconducting critical temperature of MgB_2 superconductor.

3.5. Effect of Experimental Conditions in Altering MgB_2 Superconducting Critical Temperature Using Developed SINE-ELM-RTR Model

The developed SINE-ELM-RTR model investigated the significance of experimental conditions on the superconducting critical temperature of MgB_2 superconductors, and the estimates of the developed model in each of the samples are presented in Figure 7.

Sample A in the figure represents a bulk sample of MgB_2 superconductor sintered at 650°C for one hour while sample B is a MgB_2 superconducting sample sintered at 900°C for zero minutes and then sintered at 650°C for one hour. Sample C was sintered at 900°C for ten minutes and then 650°C for an hour. Sample D underwent initial sintering at 900°C for twenty minutes and subsequent sintering at 650°C for one hour [57]. These experimental conditions introduced disorders and impurity scattering into the superconductor crystal lattice and manifested in a change of room temperature resistivity. The results of the developed SINE-ELM-RTR model that implemented this resistivity change agree excellently with the measured values [57].

Figure 7. Significance of experimental conditions on superconducting critical temperature of MgB_2 superconductor.

4. Conclusions

The superconducting critical temperature of MgB_2 superconductor doped with foreign materials was modeled in this work using an extreme learning machine (ELM) intelligence method. The developed SINE-ELM-LP and SIG-ELM-RRR models that, respectively, utilized the sine and sigmoid activation function with lattice distortion and residual resistivity ratio as model descriptors performed better than five different existing models in the literature. The developed SINE-ELM-RTR, which employed room temperature resistivity resulting from impurity scattering due to the adopted experimental conditions and incorporated dopants, demonstrated extraordinarily superior performance when compared with nine different models existing in the literature on the basis of mean absolute error metric. The developed SINE-ELM-RTR model further investigated the influence of encapsulated carbon, as well as experimental conditions on superconducting transition temperature of MgB_2 superconductor, and the obtained results agreed excellently with the measured values. The ease of implementation of the empirical functions generated by the developed models coupled with their extraordinary performance will be of immense significance in determining the superconducting critical temperature of treated or doped MgB_2 superconductor, without experimental difficulties, while a high level of precision is maintained.

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Conflicts of Interest: Authors declare no conflicting financial or non-financial interest.

Appendix A

Table A1. Weights associated with the developed SINE-ELM-RTR and SIG-ELM-RRR models.

SINE-ELM-RTR				SIG-ELM-RRR			
t	β_t	b_t	ϕ_t	n	β_n	b_n	ϕ_n
1	0.186101	0.985921	−0.49138	1	−0.94801	0.249588	$−6.6 \times 10^{11}$
2	0.971086	0.887304	−16.5318	2	−0.85068	0.087805	1.8×10^{12}
3	−0.85746	0.839137	4.556608	3	0.51173	0.982904	$−7.3 \times 10^{11}$
4	−0.18748	0.344938	−4.36868	4	0.741441	0.459048	5.65×10^{11}
5	−0.34283	0.886074	−8.27201	5	0.687243	0.739619	2.18×10^{11}
6	0.105085	0.688138	−3.7579	6	0.077477	0.025293	$−3.5 \times 10^{11}$
7	0.248612	0.321202	6.322497	7	0.811055	0.659992	$−3.2 \times 10^{11}$
8	0.046614	0.280338	3.564957	8	0.927674	0.071916	5.67×10^{11}
9	0.005162	0.069928	12.33314	9	0.243973	0.382567	$−4.1 \times 10^{11}$
10	0.657037	0.771272	−7.26767	10	0.346665	0.499726	$−6.9 \times 10^{11}$
11	0.760515	0.665401	−7.71525	11	0.807224	0.369837	$−2.4 \times 10^{11}$
12	−0.55834	0.844292	3.977303	12	0.550768	0.315007	1.16×10^{12}
13	0.497978	0.028985	8.330593	13	0.760484	0.914151	$−3.2 \times 10^{11}$
14	−0.04159	0.176893	−2.90072	14	0.198338	0.272855	$−2.5 \times 10^{11}$
15	−0.61813	0.795095	4.707716	15	−0.34972	0.217214	1.91×10^{11}
16	−0.79902	0.201458	−14.9644	16	−0.2145	0.97928	$−2.9 \times 10^{11}$
17	−0.2869	0.047778	−7.45418	17	−0.54683	0.416977	4.21×10^{11}
18	−0.86861	0.774912	−1.48456	18	−0.97811	0.62296	8.03×10^{10}
19	0.282657	0.047952	7.512496	19	−0.97086	0.908884	$−7 \times 10^{10}$
20	−0.57798	0.571814	−5.84116	20	0.65959	0.709022	3.69×10^{11}
21	0.205688	0.978185	10.38625	21	−0.32761	0.420318	$−3.9 \times 10^{11}$
22	−0.39894	0.187222	21.83146	22	0.249901	0.875519	$−5 \times 10^{11}$
23	−0.56649	0.465004	2.970312	23	0.116835	0.790609	$−1.5 \times 10^{11}$
24	0.240202	0.531042	−12.5355	24	−0.16132	0.882571	$−2.4 \times 10^{11}$
25	−0.51533	0.059517	−5.80235	25	−0.41991	0.778119	$−3.3 \times 10^{11}$
26	0.79005	0.254225	0.75258	26	−0.14931	0.812305	$−5.5 \times 10^{10}$
27	−0.51749	0.87309	−12.6099	27	−0.04007	0.936845	5.14×10^{11}
28	−0.88805	0.928452	2.058698	28	0.738756	0.227	1.25×10^{11}
29	−0.54559	0.031534	−3.15246				
30	−0.22413	0.706568	5.20531				
31	−0.19999	0.884873	2.955585				
32	−0.22367	0.36999	12.04491				
33	0.008046	0.677772	22.83283				
34	−0.48827	0.537313	−9.23591				
35	0.226645	0.782182	−22.1123				
36	−0.11027	0.824145	5.289399				
37	0.667544	0.717049	−6.7686				
38	0.209168	0.415207	2.415386				
39	0.441331	0.278097	−19.9039				
40	−0.19808	0.116406	−5.2194				

Table A2. Weights associated with the developed SINE-ELM-LP models.

SINE-ELM-LP				
j	β_j	b_j	ϕ_j (a-Axis)	ϕ_j (c-Axis)
1	−0.4997	0.652607	0.743911	$−4.2 \times 10^{10}$
2	−0.67766	0.467709	0.090015	$−2.1 \times 10^{10}$
3	−0.86377	0.954054	0.164275	$−1.2 \times 10^{11}$
4	0.683079	−0.79966	0.472316	$−1.7 \times 10^{11}$
5	−0.00979	−0.32342	0.600756	1.83×10^{11}
6	0.841091	−0.27679	0.188896	$−4.2 \times 10^{10}$

Table A2. Cont.

SINE-ELM-LP				
j	β_j	b_j	ϕ_j (a-Axis)	ϕ_j (c-Axis)
7	0.101029	−0.48301	0.927077	2.5×10^{10}
8	−0.34339	0.011686	0.639909	1.97×10^{11}
9	0.702912	−0.70551	0.210308	$−3.2 \times 10^{11}$
10	−0.02017	−0.14905	0.099793	1.24×10^{11}
11	−0.61274	0.21401	0.978095	$−2 \times 10^{11}$
12	0.018972	0.200443	0.963636	8.56×10^{10}
13	−0.0354	0.145625	0.326246	$−3.1 \times 10^{10}$
14	0.855968	−0.95176	0.862211	5.14×10^{11}
15	0.846998	0.108338	0.276779	$−3.5 \times 10^{11}$
16	−0.52748	−0.98937	0.660844	3.83×10^{11}
17	0.03233	−0.8782	0.106834	$−6.5 \times 10^{10}$
18	0.724542	−0.71074	0.628271	$−3 \times 10^{11}$
19	0.807988	−0.17671	0.572399	$−4.3 \times 10^{11}$
20	−0.85738	−0.14512	0.210892	2.33×10^{11}
21	−0.00234	−0.99127	0.284927	$−6.8 \times 10^{11}$
22	0.908775	−0.38413	0.407496	$−1.4 \times 10^{10}$
23	−0.47597	−0.33637	0.810187	$−8.9 \times 10^{10}$
24	0.762863	−0.73716	0.770142	$−2.7 \times 10^{11}$
25	0.981362	0.975124	0.705181	8.28×10^{10}
26	−0.99383	0.542196	0.9007	$−1.2 \times 10^{10}$
27	0.092747	−0.49115	0.275874	5.07×10^{10}
28	−0.57273	0.184956	0.167006	$−1.2 \times 10^{11}$
29	−0.65152	−0.5996	0.550787	9.05×10^{10}
30	0.282282	−0.33706	0.817289	$−6.7 \times 10^{10}$
31	−0.76051	0.798628	0.193159	2.29×10^{11}
32	−0.6003	0.624115	0.041467	2.72×10^{11}
33	−0.1782	0.644477	0.753259	$−2.2 \times 10^{11}$
34	−0.10475	−0.22332	0.958517	3.11×10^{11}
35	0.378573	0.021686	0.811174	1.8×10^{11}
36	0.545292	−0.78463	0.507292	$−1.1 \times 10^{11}$
37	−0.58192	0.72754	0.874458	$−7 \times 10^{10}$
38	0.191821	0.419286	0.676789	3.14×10^{11}
39	0.477935	0.678581	0.459807	$−1.1 \times 10^{10}$
40	0.180476	−0.80014	0.417125	1.56×10^{11}
41	0.901989	−0.443	0.943964	$−9 \times 10^{10}$
42	−0.78219	−0.30558	0.137807	$−8.4 \times 10^{10}$
43	0.935107	0.931112	0.847502	2.8×10^{10}
44	0.057323	0.670175	0.885394	$−2.5 \times 10^{10}$
45	−0.93104	0.655237	0.629661	3.97×10^{11}
46	−0.8676	0.348332	0.991742	$−5.8 \times 10^{11}$
47	−0.91624	−0.91311	0.483752	$−1.6 \times 10^{11}$
48	−0.39467	0.574348	0.347083	6.17×10^{10}
49	−0.31988	0.892922	0.175956	2.04×10^{11}
50	−0.18228	−0.92657	0.599345	2.24×10^{11}
51	−0.92256	−0.49886	0.003855	$−5.2 \times 10^{10}$
52	0.766784	−0.86108	0.899305	1.49×10^{10}
53	−0.54562	0.228554	0.987931	$−6.4 \times 10^{10}$
54	0.243102	−0.56612	0.796928	$−1.5 \times 10^{11}$
55	0.405998	0.635474	0.872865	7.19×10^{10}
56	0.962473	0.683905	0.792791	$−1 \times 10^{12}$
57	0.114881	0.830181	0.518729	$−4.9 \times 10^{10}$
58	0.561707	−0.87433	0.08746	1.23×10^{11}
59	−0.72095	−0.97267	0.55657	$−6.1 \times 10^{11}$
60	0.975459	0.320788	0.312556	5.91×10^{11}
61	0.542332	0.052646	0.124194	9.85×10^{11}

Table A2. Cont.

SINE-ELM-LP				
j	β_j	b_j	ϕ_j (a-Axis)	ϕ_j (c-Axis)
62	−0.08299	−0.50068	0.947863	1.42×10^{11}
63	−0.37536	−0.7719	0.065324	3.16×10^{11}
64	0.36288	−0.1862	0.901494	3.36×10^{10}
65	0.545377	0.564987	0.922426	8.39×10^{10}
66	−0.57065	0.609115	0.698265	1.11×10^{11}
67	0.237133	−0.65181	0.083918	8.69×10^{10}
68	−0.07771	0.330392	0.379303	$−1.6 \times 10^{10}$

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