JOURNAL OF NANO- AND ELECTRONIC PHYSICS Vol. **16** No 4, 04018(6pp) (2024)
ЖУРНАЛ НАНО- ТА ЕЛЕКТРОННОЇ ФІЗИКИ Том **16** № 4, 04018(6cc) (2024)

REGULAR ARTICLE

Novel AI-Based Methodology for Predicting Superconducting Films' Resistance-Temperature Properties with Nanomaterials

Gaurav Kumar[1,*] ✉, Komal Parashar[2], Prashant Sharma[3], Durgeshwar Pratap Singh[4], Anurag Shrivastava[5], Arun Pratap Srivastava[6], Amit Srivastava[7], P. William[8]

[1] *Chitkara Centre for Research and Development, Chitkara University, 174103 Himachal Pradesh, India*
[2] *Centre of Research Impact and Outcome, Chitkara University, Rajpura-140417 Punjab, India*
[3] *Department of Civil Engineering, GLA University, Mathura-281406, Uttar Pradesh, India*
[4] *Department of Mechanical Engineering, Graphic Era Deemed to be University, Dehradun, Uttarakhand*
[5] *Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, TN, India*
[6] *Lloyd Institute of Engineering & Technology, Greater Noida, Uttar Pradesh 201306, India*
[7] *Lloyd Law College, Greater Noida, Uttar Pradesh 201306, India*
[8] *Department of Information Technology, Sanjivani College of Engineering, Kopargaon, MH, India*

(Received 18 April 2024; revised manuscript received 21 August 2024; published online 27 August 2024)

Integrating state-of-the-art nanostructures into prediction models enhances our understanding of superconductivity properties. Using artificial intelligence techniques and modeling, the mathematical method leverages the unique characteristics of nanoparticles to improve resistance-temperature projections. This paper proposes a novel artificial intelligence (AI) approach for predicting the resistance-temperature aspects of nanomaterial-infused superconducting films. In this paper, we offer a novel AI method called Progressive Red Fox Optimized Adaptive Decision Tree (PRFO-ADT) to predict the super conductiveness of film coatings. A sufficient information pretreatment step that addresses issues like feature creation and normalizing is part of the study's technique. A diversified dataset is employed, including synthesis factors, nanomaterial properties, and resistance-temperature patterns of several superconducting films. Next, the gathered data undergo the preprocessing stage using a min-max normalization. Our proposed method opens the door to a sophisticated comprehension of the resistance-temperature landscapes of their superconductivity films by investigating several nanotechnologies and their different effects on the prediction algorithm. Compared to other existing approaches, PRFO-ADT is efficient and produces a lower rate of errors, with a total of 1.2 RMSE, 1.25 MSE, 1.1 MAPE, and 4.8s of computing time.

Keywords: Nanomaterial, Superconductivity, Nanotechnology, Resistivity, Film resistance.

DOI: 10.21272/jnep.16(4).04018 PACS numbers: 73.40.Cg, 84.37.+q

1. INTRODUCTION

Superconductivity is an intriguing phenomenon in material research, and the universe whereby certain materials exhibit little resistance to electrical current and magnetic release once refrigerated below an acceptable degree. This special characteristic offers important ramifications for many technological uses, such as quantum information processing, imaging in medicine, and energy transfer. Creating magnetic coatings with reliable and repeatable characteristics was a major obstacle using superfast for useful purposes [1]. Comprehending and forecasting the capacitance using super films is a prerequisite improving efficiency and incorporating into practical uses, a blend of innovative substance-synthesizing processes, empirical methodologies, and theoretical frameworks [2]. In this environment, scientists seek a grasp of the various elements, such as substance composition, crystal arrangement, and external electric fields that affect the capacitance from superconductivity layers. The range of temperatures when a substance turns superconductivity has been referred to the critical temperatures. Determining the temporal dependence of the resistivity is crucial for characterizing magnetic materials. The crystal layout and chemistry of superconductivity materials are key factors in defining their superconductivity characteristics [3]. The electron-atom partnering that underlies superconducting may be influenced by the kind of substances available and also the configuration of molecules. The electrical attributes of a magnetic layer may be affected by its width. Comprehending resistance

* Correspondence e-mail: gauravcivilengg714@gmail.com

Cite this article as: G. Kumar et al., *J. Nano- Electron. Phys.* 16 No 4, 04018 (2024) https://doi.org/10.21272/jnep.16(4).04018

that affects film thickness is essential when creating materials with particular uses in sight. The Meissner execution of this occurrence, it happens whenever superconducting releases fields of magnetism. It may be affected at temps around by the reaction beyond an electric outside [4]. Anticipating behavior could be crucial for functions like microwave detecting and drifting. With its unparalleled potential to control and create metals across tiny levels, the discipline of nanoparticles has ushered in an exciting period of creativity in metals research. Despite the myriad applications of nanotechnologies, temperature-sensitive properties remain interesting [5]. To use nanoparticles in a wide range of fields, including gadgets, energy storage, healthcare, and catalytic processes, it is essential to comprehend that they react to temperature changes [6]. In contrast with their mass parallels, nanostructures have distinct and frequently improved thermal characteristics [7]. Customized implementations in many domains are made possible by the distinctive features connected with temperatures that are introduced by manipulating dimensions, form, and nanotechnology. Fascinating the areas of non-material's values that exhibit's dynamical relationship between structure, parameters, and thermodynamics responses[8].The objective of the study is to provide the temperature-sensitive characteristics of superconductivity layers are influenced by the dimension, framework, and makeup of nanoparticles. The contact between surfaces and quantum changes applies at the microscopic level.

2. RELATED WORK

The study [9] examined the link among the variables of laser pulses along with the superconductivity temperature at which transition occurs and the resistivity ratios during lasers layer depositing, use a model composed of multiple linear regressions. The research [10] discovered the methods to simplify the process of getting these data are partially disregarded. In this study, advocate for extrapolation using approximate approaches rather than assessing. The article [11] suggested that the certain recent articles that physically measuring such curves constitute a laborious and expensive procedure that grows tiresome whenever repeatedly across a broad spectrum of values. Additionally, experts assess both versions in relation to the degree of accuracy that has been achieved. The study [12] explored the real-world processes that the computational modeling and testing techniques to gauge dynamical resistance. It is possible to evaluate the fluctuating resistances losses for a basic superconductivity topography using quantitative formulas. The research [13] presented the temperatures relationship for the electromagnetic penetration level was in line with the properties of an open s-wave superconductor. Applications requiring strong dynamic induction, including qualitative susceptibility sensors and microwave kinetics capacitance sensors, ought to use boron-doped diamond sheets. The article [14] investigated the large collection of information using niobium-nitride-based Nano wire type superconductivity of single-photon sensors has been collected to determine the theoretical connection among efficiency with impedance each squared in normal conditions. The expected drop in energy needed to achieve almost flawless light identifying detection precision. The study [15] derived the theories of assumptions accord about reports on films, allowing an accurate derivation of estimated quantum particles inelastic dispersion durations and heating ratios.. The research [16] derived the niobium that comprises the multiple oxides with gallium possesses as single titanium was the kinds of consistency along with the grade of native surfaces oxides are the crucial factors. For many years the two-level structures origins are the edges as well as contacts were linked to super qubits.

3. METHODOLOGY

Anticipate and optimize the resistance-temperature characteristics of superconductivity films to establish the groundwork towards the creation of new technology. Facilitate the progress of technology, power transfer, and many other domains wherein superconducting have significant importance. Figure 1 depicts the flow of the suggested methodology as superconductivity data set was gathered, and the data set was preprocessed through the min-max normalizations, then Progressive Red Fox Optimized adaptive Decision Tree (PRFO-ADT) was proposed to analyze the results.

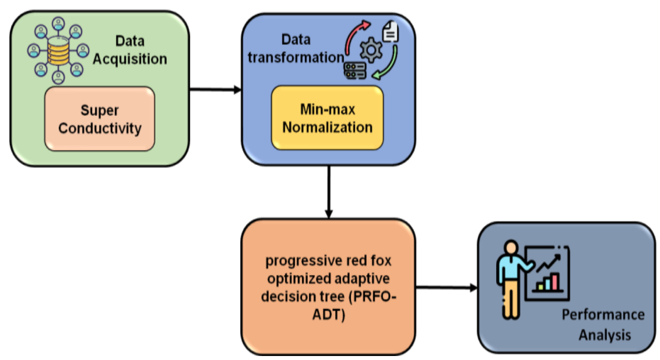

Fig. 1 – Flow of methodology

3.1 Dataset

Using pulsing laser energy, NbN sheets with densities spanning from 10nanometer to 100nanometer have been applied onto c-cutsurfaces maintained a uniform simmering point at 600 degree Celsius [19].

3.2 Data Preprocessing Using Min-Max Normalization

Min-Mix Normalization is a method that applies a linear change to the initial set of information. The term Min-Mix Normalization refers to a method that preserves the relationships between the initial information. An easy method called min-max normalization allows information to be fitted in a predetermined border that has a predetermined border. Using the Min-Max normalization method as shown in equation (1);

$$B' = \left(\frac{B - \min\ value\ of\ B}{\max value\ of\ B - \min\ value\ of\ B}\right) * (C - D) + D \quad (1)$$

Where by B' contains one of the Min-Max normalized pieces of data. If $[C]$determines the predetermined border, and if B is an initial information area, B is newly translated information.

3.3 Progressive Red Fox Optimized Adaptive Decision Tree (PRFO-ADT)

3.3.1 Progressive Red Fox Optimized (PRFO)

PRFO metaheuristics and optimization technique that drew an involvement during foraging, PRFO approach among lurks beyond shrub attacks. This method involves exploiting as well as investigating the previous metaheuristic explorations that were characterized through NRF as the expression. The term exploitation was established as near with its sources available. Using randomized person generations, the PRFO is characterized by the following characteristics shown in equation (2):

$$W = [w_0, w_1, \ldots\ldots, w_{m-1}] \quad (2)$$

Where j denotes the people populations$\left(W_i^j\right)^s$ explains w_j among iterations s and i were the dimensions in searching spaces. By assuming e as conditioning functions as Q^m, which m stands for parameters $m$as it ranges $[b, a]^m$as shown in equation (3):

$$(W)^j = \left[(w_0)^j, (w_1)^j, \ldots\ldots, \left(w_{m-1)}\right)^j\right] \quad (3)$$

People are considered to have a specific task to assist the team in research. Consequently, people change depending on their monetary values. If there is a lack of prey in particular location, the people go to another area for greater probabilities of pursuing predators. In this case, the inverse of the distance calculated by Euclid is used, where $b, a \in Q$ as shown in equation (4):

$$C\left(\left((W)^j\right)^s, (W_{best})^s\right) = \sqrt{((W)^j)^s - (W_{best})^s} \quad (4)$$

Thus, every applicant should move using the best option as follows in equation (5):

$$((W)^j)^s = ((W)^j)^s + \alpha \times sgn\ ((W_{best})^s - \left((W)^j\right)^s) \quad (5)$$

For this scenario, the applicant's current residence should present an appropriate choice. Its red-furred fox observes the object and moves toward it. It is characterized by the use of the progressive red foxes optimization method that is demonstrated using any value for r between $[0, 1]$ as shown in equation (6):

$$\begin{cases} move\ closer\ \ if\ q > \frac{3}{4} \\ stay\ and\ hide\ \ if\ r \leq \frac{3}{4}. \end{cases} \quad (6)$$

The component of movements is determined using $[0, 0.2]$ were upgraded a cichloid formulation. The subsequent phase is affected $\phi_0$with a parameter, known as diameter that depends on a pair of parameters a, which is an arbitrary number $[0,2\pi]$in the range of values, and the parameter that reflects the component. A number inside the bounds of fox viewing area, this phrase could be represented in equation (7):

$$q = \begin{cases} b \times \frac{\sin(\phi_0)}{\phi_0} & , if\ \phi_0 \neq 0 \\ \gamma,\ \ if\ \phi_0 = 0 \end{cases} \quad (7)$$

To maintain a stable proportion of the community, five percent of the most detrimental people in the newly generated population were culled, whereas numerous additions were added. In iteration, additional optimal individuals were obtained as the alpha pair. The area around the core is determined as shown in equation (8):

$$G_d^s = \frac{1}{2}(W(1))^s(W(2))^s \quad (8)$$

As well as the Euclidean radius is also used to determine the territory's perimeter as shown in equation (9):

$$G_c^s = \sqrt{\left(W(1)\right)^s - \left(W(2)\right)^s} \quad (9)$$

In a hypothetical situation, randomly between 0 and 1, as shown in equation (10):

$$\begin{cases} New\ nomadic\ candidate,\ \ if\ \sigma > 0.45, \\ Reproduction\ of\ the\ alpha\ couple, if\ \sigma \leq 0.45 \end{cases} \quad (10)$$

In the quest for time, arbitrary locations are found. The most recent membership gets established through selection as, shown in equation (11):

$$(W^{rep})^s = \frac{\sigma}{2}\left(W(1)\right)^s - \left(W(2)\right)^s \quad (11)$$

The research's PRFO settings were follows $b = 0.2\ \ \phi_0 = 1$.

3.3.2 Adaptive Decision Tree (ADT)

An Adaptive decision tree (ADT) constitutes an effective and visually appealing utilized which provides an organized depiction of potential results and the choice routes which lead to them. It is employed for data assessment and choice-making. Especially useful in disciplines like company analytics, and neural networks was this simple approach. Figure 2 depicts the flow of decision tree. A tree of decisions is conceptualized as roots which represents the original selection or beginning points and branching outward across multiple points at every stage of decision-making to indicate other options or possible results. The twigs keep growing, creating a living thing which assists clearly and methodically illustrating the process of making choices.

4. RESULT

The resistance temperature characteristic the superconductivity material that enhances the comprehension of mechanisms underlies the changes. It is improves the prediction algorithm's resilience and flexibility to manage a variety of unpredictable situations and guarantee that is applicable in a variety of contexts. It provides a useful and workable alternative across materialists and investigators that allows for higher quality estimations of the resistivity of superconductivity sheets throughout a range of technical usages. In this paper, we used progressive red fox optimized adaptive decision tree (PRFO-ADT) as a proposed method and existing methods like "hybridizes genetic algorithm support vector regression room temperature resistivity (HGA-SVR-RTR), hybridizes genetic algorithm support vector regression residual resistivity ration (HGA-SVR-RRR), and hybridizes genetic algorithm support vector regression structural lattice distortion(HGA-SVR-SLD)".

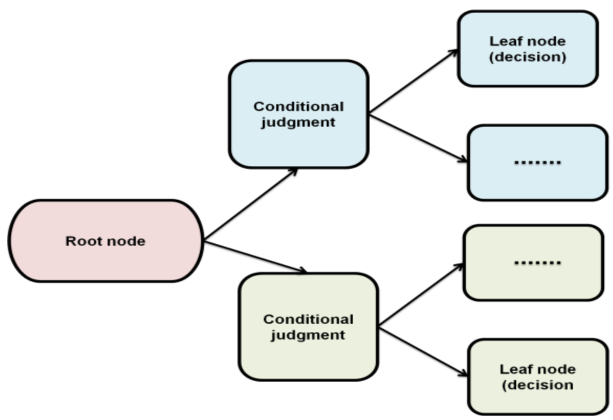

Fig. 2 – Flow of adaptive decision tree structure

Root mean square error (RMSE) is a statistics indicator that measures the discrepancies among expected and real information to evaluate a prediction algorithm's efficiency. RMSE is an accurate measure of the mean amount of impedance predictions failures in the setting of superconductivity films impedance predictions. RMSE shows reduced variances in expected and reality, which is a sign of higher accuracy in forecasting. A greater RMSE indicates greater predicting mistakes. In order to enhance and strengthen prediction skills, scientists and engineers of RMSE utilize to assess that simulations capture the fundamental trends in resistant information related to superconductivity coatings. Figure 3 and Table 1 illustrates the value of RMSE has occurred lower value in PRFO-ADT that obtained 1.2, which is more efficient for managing the superconductivity of film resistance and other methods obtained 1.3 in HGA -SVR-RTR, 2.0 in HGA -SVR-RRR, and 1.6 revealed in HGA -SVR-SLD.

Table 1 – Numerical outcomes of RMSE

Methods	RMSE
HGA-SVR-RTR [20]	1.3
HGA-SVR-RRR [20]	2.0
HGA-SVR-SLD [20]	1.6
PRFO-ADT(Proposed)	1.2

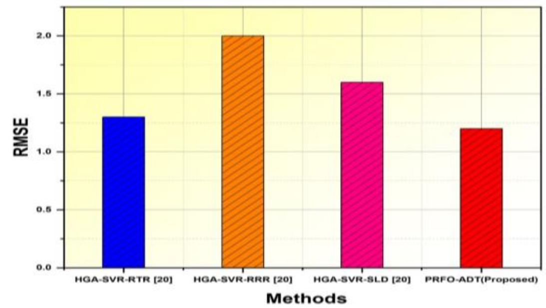

Fig. 3 – Performance analysis of RMSE

Mean square error (MSE) is a vital indicator for assessing the prediction model's effectiveness. The average squared discrepancies among the resistivity levels that were anticipated and those resistivity levels that occurred in the superconductivity layers have been measured. MSE highlights greater mistakes and criminalizes these with greater severity through square the disparities among the expected and real numbers. In order to evaluate the algorithm dependability and determine that the degree to represents the fundamental trends of information, it is vital to comprehend MSE in a setting of forecasting the conductivity of superconductivity layers. Table 2 and Figure 4 depict the value of MSE for PRFO-ADT of 1.25, 1.4 for HGA-SVR-RTR, and 2.1 for HGA-SVR-RRR, and 1.8 revealed for HGA-SVR-SLD.

Table 2 – Numerical outcome of MSE

Methods	MSE
HGA-SVR-RTR [20]	1.4
HGA-SVR-RRR [20]	2.1
HGA-SVR-SLD [20]	1.8
PRFO-ADT(Proposed)	1.25

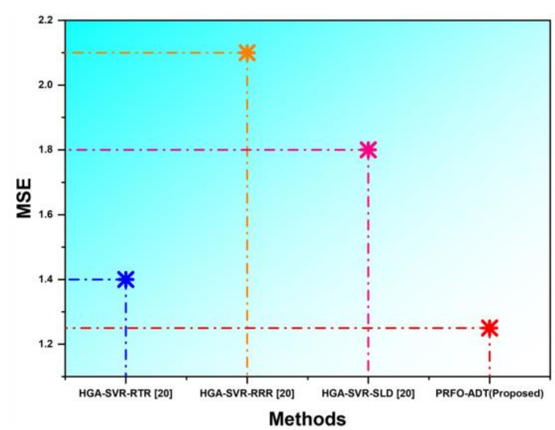

Fig. 4 – Performance analysis of MSE

5. CONCLUSION

Predicting the resistance-temperature characteristics of nonmaterial based superconductivity coatings was a complex procedure that blends mathematical methods alongside modern material research. A comprehensive strategy for simulation creation is required due to the novel possibilities and problems presented by the incorporation of nanotechnology. The creation of theoretical predictive models, whereby algorithmic selections were conditioned on the processed information, that captures the intricate relationships between the resistance-temperature variables in superconducting levels and the characteristics of Nano materials were an essential phase in the procedure's development. The amount of computer power needed for this phase depends on how many representations are employed. In overall, calculations take longer when variables are adjusted and when modeling is refined repeatedly. Once created these models predict, the abilities of new perspectives on superconductivity layers that behave at different temperatures, providing crucial knowledge for the development and engineering of materials. Nonetheless, the achievement of these forecasts relies on the meticulous assessment of the complexities of nanomaterials and the prudent use of modeling methodologies.

REFERENCES

1. K. Ienaga, T. Hayashi, Y. Tamoto, S. Kaneko, S. Okuma, *Phys. Rev. Lett.* **125** No 25, 257001 (2020).
2. Z. Sun, T. Oseroff, Z. Baraissov, D.K. Dare, K. Howard, B. Francis, A.C. Hire, N. Sitaraman, T.A. Arias, M.K. Transtrum, R. Hennig, *Adv. Electron. Mater.* **9** No 4, 2300151 (2023).
3. M. Durkin, R. Garrido-Menacho, S. Gopalakrishnan, N.K, Jaggi, J.H. Kwon, J.M. Zuo, N. Mason, *Phys. Rev. B* **101** No 3, 035409 (2020).
4. W. Chen, S. Ito, N. Yusa, H. Hashizume, *Fusion Eng. Design* **148**, 111284 (2019).
5. S. Lee, J.H. Kim, Y.W. Kwon, *arXiv preprint arXiv:2307.12008* (2023).
6. E.M. Baeva, A.I. Kolbatova, N.A. Titova, S. Saha, A. Boltasseva, S. Bogdanov, V. Shalaev, A.V. Semenov, A. Levchenko, G.N. Goltsman, V.S. Khrapai, *arXiv preprint arXiv:2202.06309* (2020).
7. E. Snider, N. Dasenbrock-Gammon, R. McBride, X. Wang, N. Meyers, K.V. Lawler, E. Zurek, A. Salamat, R.P. Dias, *Phys. Rev. Lett.* **126** No 11, 117003 (2021).
8. X. Zhang, X. Shi, *J. Supercond. Novel Magn.* **33**, 217 (2020).
9. Y. Zhang, X. Xu, *Physica C* **592**, 1353998 (2022).
10. T. Akram, S.R. Naqvi, S.A. Haider, M. Kamran, A. Qamar, *Superlattice. Microst.* **145**, 106635 (2020).
11. T. Akram, S.R. Islam, S.R. Naqvi, K. Aurangzeb, M. Abdullah-Al-Wadud, A. Alamri, *Res. Phys.* **24**, 104088 (2021).
12. H. Zhang, B. Shen, X. Chen, Z. Jiang, *Supercond. Sci. Technol.* **35** No 11, 113001 (2022).
13. B. Oripov, D. Kumar, C. Garcia, P. Hemmer, T. Venkatesan, R. Rao, S.M. Anlage, *Appl. Phys. Lett.***118** 242601 (2021).
14. P.I. Zolotov, A.V. Semenov, A.V. Divochiy, G.N. Goltsman, N.R. Romanov, T.M. Klapwijk, *IEEE Trans. Appl. Supercond.* **31** No 5, 2400305 (2021).
15. A.I. Bezuglyj, V.A. Shklovskij, R.V. Vovk, V.M. Bevz, M. Huth, O.V. Dobrovolskiy, *Phys. Rev. B* **99** No 17, 174518 (2019).
16. C. Koppel, B. Wilfong, A. Iwanicki, E. Hedrick, T. Berry, T.M. McQueen, *Inorganics* **11** No 3, 117 (2023).

Нова методологія на основі ШІ для прогнозування властивостей опору та температури надпровідних плівок за допомогою наноматеріалів

Gaurav Kumar[1], Komal Parashar[2], Prashant Sharma[3], Durgeshwar Pratap Singh[4], Anurag Shrivastava[5], Arun Pratap Srivastava[6], Amit Srivastava[7], P. William[8]

[1] *Chitkara Centre for Research and Development, Chitkara University, 174103 Himachal Pradesh, India*
[2] *Centre of Research Impact and Outcome, Chitkara University, Rajpura-140417 Punjab, India*
[3] *Department of Civil Engineering, GLA University, Mathura-281406, Uttar Pradesh, India*
[4] *Department of Mechanical Engineering, Graphic Era Deemed to be University, Dehradun, Uttarakhand*
[5] *Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, TN, India*
[6] *Lloyd Institute of Engineering & Technology, Greater Noida, Uttar Pradesh 201306, India*
[7] *Lloyd Law College, Greater Noida, Uttar Pradesh 201306, India*
[8] *Department of Information Technology, Sanjivani College of Engineering, Kopargaon, MH, India*

Інтеграція найсучасніших наноструктур у моделі прогнозування покращує наше розуміння властивостей надпровідності. Використовуючи методи штучного інтелекту та моделювання, математичний метод використовує унікальні характеристики наночастинок для покращення прогнозів опору та температури. У цьому документі пропонується новий підхід штучного інтелекту (ШІ) для прогнозування аспектів опору та температури надпровідних плівок, наповнених наноматеріалами. У цій статті ми пропонуємо новий метод штучного інтелекту під назвою прогресивне оптимізоване адаптивне дерево рішень Red Fox (PRFO-ADT) для прогнозування надпровідності плівкових покриттів. Етап попередньої обробки достатньої інформації, який стосується таких проблем, як створення ознак і нормалізація, є частиною методики дослідження. Використовується різноманітний набір даних, включаючи коефіцієнти синтезу, властивості наноматеріалів і моделі опору-температури кількох надпровідних плівок. Далі зібрані дані проходять етап попередньої обробки з використанням мінімально-максимальної нормалізації.

Запропонований нами метод відкриває двері для складного розуміння ландшафтів опору та температури їхніх надпровідних плівок шляхом дослідження кількох нанотехнологій та їх різного впливу на алгоритм прогнозування. Порівняно з іншими існуючими підходами, PRFO-ADT є ефективним і створює нижчий рівень помилок із загальним значенням 1,2 RMSE, 1,25 MSE, 1,1 MAPE і 4,8 с часу обчислення.

Ключові слова: Наноматеріал, Надпровідність, Нанотехнологія, Питомий опір, Стійкість плівки.