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REGULAR ARTICLE

Prediction of Electrical Conductivity of Polymer Nanocomposites Using Fuzzy Logic-Based Approach of Artificial Intelligence

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This study investigates the electrical conductivity of polymer nanocomposites filled with carbon nanotubes, taking into account the influence of both nanotube concentration and diameter. The experimental results reveal a pronounced nonlinear dependence of conductivity on filler content, characterized by a transition from a tunneling-dominated charge transport mechanism at low concentrations to a percolation-controlled regime after the formation of a continuous conductive network. It is shown that the nanotube diameter significantly affects the conductivity over the entire concentration range, particularly in the pre-percolation region, which can be attributed to variations in interparticle contact efficiency and tunneling conditions. A comparative analysis of the experimental data was performed using classical analytical models, including percolation-based approaches and the McLachlan generalized effective medium model. It was found that these models can adequately describe individual conductivity curves; however, their fitting parameters vary substantially with nanotube diameter and often lose physical interpretability. This limitation restricts their applicability for the unified description and prediction of electrical behavior in systems with varying geometrical characteristics of the filler. To overcome these limitations, an intelligent model of electrical conductivity based on fuzzy logic has been developed, which allows simultaneously taking into account the concentration and diameter of nanotubes without the need to specify a rigid analytical dependence. The proposed modeling approach provides high accuracy of reproduction of experimental data and forms a generalized description of the dependence of electrical conductivity on system parameters. The results obtained confirm the effectiveness of the application of artificial intelligence methods for modeling and predicting the properties of complex polymer nanocomposites under conditions of limited experimental data.

Keywords: Polylactic acid, Polymer nanocomposites, Carbon nanotubes, Electrical conductivity, Artificial Intelligence, Fuzzy Logic Models.

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1. INTRODUCTION

Polymer nanocomposite materials filled with carbon nanotubes (CNTs) have attracted considerable attention of researchers in recent decades due to the combination of low density, processability of the polymer matrix and unique electrophysical properties of the nanofiller [1]. Of particular interest are electrically conductive polymer nanocomposites, which are used in flexible electronics, sensor systems, electromagnetic radiation screens, antistatic coatings and energy devices [2, 3]. The electrical conductivity of such materials is formed as a result of the complex interaction of geometric, structural and physical factors that determine the process of formation of a conductive network in the polymer matrix. Among biodegradable polymers, a promising matrix for the creation of such materials is polylactic acid (PLA), which combines environmental safety, biocompatibility and good technological characteristics [4, 5].

To describe the electrical conductivity of polymer nanocomposites, analytical models are traditionally used, which can be conditionally divided into two main classes: effective medium models and percolation models. Effective medium models, in particular the generalized Bruggeman model, consider the composite as a homogenized system with effective properties determined by the ratio of phases and their individual characteristics [6]. Percolation models, in turn, are based on the theory of critical phenomena and describe a sharp transition from an insulating to a conducting state when the percolation threshold is reached, using power dependences with universal critical indices [7].

Despite the success of these approaches in explaining general patterns, they have significant limitations when applied to real polymer nanocomposites with CNTs. This is primarily due to the fact that such models are based on a number of simplified assumptions, in particular regarding the homogeneity of the filler distribution, the isotropy

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of the system and the idealized geometry of the conducting particles. In real materials, the structure is much more complex: aggregation of nanotubes, variations in their length and diameter, as well as a significant influence of interparticle contacts and tunneling transitions on the charge transfer mechanism are observed [8].

One of the key, but insufficiently taken into account parameters is the geometric characteristics of nanotubes, in particular their diameter. The diameter of the CNT determines the curvature of the surface, the area of interfacial contact with the polymer matrix, the effective distance between the conducting elements and the nature of electronic tunneling between them [9]. Despite the obvious physical significance of this parameter, most existing analytical models do not include it explicitly or only indirectly through generalized effective parameters. This significantly limits their ability to adequately describe and predict the properties of systems with different types of nanotubes.

In this regard, recently, approaches based on artificial intelligence and machine learning methods have been actively developed, which allow modeling complex nonlinear dependencies without the need for explicit formulation of physical equations [10]. Such models are able to take into account multidimensional relationships between system parameters, including concentration, geometric characteristics of the filler and material processing conditions. However, the effectiveness of commonly used deep learning and machine learning methods significantly depends on the volume and representativeness of training data. In the case of polymer nanocomposites, experimental data are often limited, which reduces the reliability and generalizability of such models. A promising alternative in conditions of limited samples are models based on fuzzy logic, which combine elements of formalized knowledge and empirical data [11]. Fuzzy models allow describing complex nonlinear systems using linguistic rules of the "if–then" type, while ensuring interpretability and resistance to data uncertainty [12]. An important advantage of this approach is the ability to integrate a priori physical ideas about the system with experimental results, which is especially relevant for multifactorial nanocomposite materials.

In this context, the aim of this work is to develop a model of the electrical conductivity of polymer nanocomposites filled with carbon nanotubes using fuzzy logic-based approach of artificial intelligence. The proposed model is aimed at taking into account key parameters of the system, in particular the concentration and diameter of nanotubes, and should provide a more adequate description of experimental dependencies compared to classical analytical approaches.

2. THEORETICAL MODELS FOR PREDICTING ELECTRICAL CONDUCTIVITY

2.1 Selection of Data for Modeling

A system based on polylactide and carbon nanotubes was chosen for modeling. To correctly build the model, the dependence of the tensile strength on the content and size of nanotubes for this system was analyzed [13-18]. Table 1 shows the average values.

Table 1 – Data set used for further modelling

No	d, nm	C, %	σ, S/cm
1	9.5	0	$1.0\cdot10^{-12}$
2	9.5	0.5	$2.0\cdot10^{-4}$
3	9.5	1	$1.3\cdot10^{-3}$
4	9.5	3	$3.0\cdot10^{-1}$
5	9.5	4.5	$5.0\cdot10^{-1}$
6	9.5	6	1.5
7	11	0	$1.0\cdot10^{-9}$
8	11	1	$1.0\cdot10^{-1}$
9	11	3	$2.5\cdot10^{-1}$
10	11	5	$4.6\cdot10^{-1}$
11	11	7	$2.\cdot10^{-1}$
12	15	0	$1.0\cdot10^{-9}$
13	15	0.25	$7.0\cdot10^{-9}$
14	15	0.5	$8.0\cdot10^{-8}$
15	15	1	$2.0\cdot10^{-4}$
16	15	1.5	$6.0\cdot10^{-4}$
17	15	2	$1.0\cdot10^{-2}$
18	15	3	$3.0\cdot10^{-2}$
19	20	0	$7.3\cdot10^{-8}$
20	20	1.5	$1.4\cdot10^{-3}$
21	20	3	$7.9\cdot10^{-2}$
22	20	6	2.1

In the modeling process, the range of carbon nanotube diameters was selected as 9.5-20 nm, which corresponds to the typical parameters of multi-walled nanotubes, which are most often used in polymer composites.

The concentration range of 0.25-7 wt. % CNT was selected taking into account the characteristic regularities of the formation of electrically conductive percolation structures in polymer nanocomposites. According to numerous studies, it is at this content of nanotubes that a spatial network of nanotubes is formed, which significantly improves the electrical conductivity of the material [19]. This allows achieving the maximum value of the electrical conductivity coefficient, which is crucial for the practical application of such materials.

Melt mixing was chosen as the main method for obtaining composites, since this approach is one of the most technologically suitable and widely used methods of introducing nanofillers into thermoplastic polymers.

2.2 Analytical Models

For a more complete and correct description of the percolation transition in nanofilled polymer systems, the McLachlan equation is used [20]:

$$(1-p)\frac{\sigma_m^{1/s}-\sigma_{DC}^{1/s}}{\sigma_m^{1/s}+A\sigma_{DC}^{1/s}}+p\frac{\sigma_f^{1/t}-\sigma_{DC}^{1/t}}{\sigma_f^{1/t}+A\sigma_{DC}^{1/t}}=0 \qquad (1)$$

This equation is a phenomenological relationship between σ_f, σ_m and σ_{DC} which are the conductivities of the nanofiller, polymer matrix, and nanocomposite, respectively. It should be noted that Eq. (1) can include both complex quantities σ_{DC}, σ_f and σ_m, and their real parts. The value of the volume fraction p lies in the range from 0 to 1, when $p=0$ the medium is nonconductive ($\sigma_{DC}=\sigma_m$), and when $p=1$ the medium

becomes conductive ($\sigma_{DC} = \sigma_f$). The critical volume fraction p_c or percolation threshold characterizes the transition from the nonconductive to the conductive state and determines the coefficient $A = (1 - p_c) / p_c$. At $s = t = 1$, this equation is transformed into the Bruggeman equation for a symmetric medium. Equation (1) has two solutions:

$$|\sigma_f| \to \infty \ : \ \sigma_{DC} = \sigma_m \left(\frac{p_c}{(p_c - p)} \right)^s, \quad p < p_c, \tag{2}$$

$$|\sigma_m| \to 0 \ : \ \sigma_{DC} = \sigma_f \left(\frac{p - p_c}{(1 - p_c)} \right)^t, \quad p > p_c, \tag{3}$$

where s and t are critical indices. Equations (2) and (3) are the reduced percolation equations.

2.3 Description of the Algorithm for Building an AI-Based Model

A critical bottleneck in the development of approximation-oriented AI models for modeling and predicting the electrical properties of polymer nanocomposites lies in the severe scarcity of experimentally obtained data, primarily due to the high cost, labor intensity and technological complexity of conducting physical experiments [10]. Under such data-constrained conditions, conventional deep learning architectures, as well as widely used machine learning techniques (including support vector machines, random forest, gradient boosting methods, and Gaussian process regression) exhibit substantial limitations in terms of generalization capability, robustness, and susceptibility to overfitting. These methods typically rely on large-scale, high-quality datasets to capture complex nonlinear relationships inherent in nanocomposite systems, which are often unattainable in practical materials science applications [10]. In contrast, fuzzy logic-based approaches offer a promising alternative paradigm due to their inherent ability to effectively formalize and process small, imprecise, and heterogeneous datasets [11]. By leveraging linguistic variables and rule-based inference mechanisms, fuzzy systems enable the construction of compact and interpretable models that preserve essential physical insights [21]. Moreover, the resulting knowledge representation in the form of transparent rule bases facilitates human interpretability and expert validation, thereby providing not only predictive capability but also explanatory value, which is critically important for the design and optimization of advanced polymer nanocomposites.

Among the wide spectrum of fuzzy modeling techniques, Takagi-Sugeno (TS) fuzzy models represent a particularly effective and well-balanced choice, as they provide a favorable trade-off between interpretability and approximation accuracy [22]. Unlike purely linguistic Mamdani-type systems, TS models employ clearly numerical consequents, enabling them to capture complex nonlinear dependencies with higher precision while still retaining a transparent rule-based structure [23]. This hybrid nature makes them especially suitable for modeling the electrical behavior of polymer nanocomposites, where both predictive performance and physical interpretability are of paramount importance. In this study, the Takagi-Sugeno fuzzy model is developed and investigated. The optimized structural and parametric configuration of the presented TS model makes it possible to achieve enhanced predictive accuracy while preserving logical transparency and interpretability of the resulting rule base.

3. RESULTS AND DISCUSSION

3.1 Generalized Effective Medium Model for Conductivity Prediction

The experimental conductivity-concentration dependences were additionally analyzed using the generalized effective medium (GEM) model proposed by McLachlan, which is widely applied for describing transport properties of heterogeneous systems near the percolation threshold. In the present study, an explicit asymptotic form of the GEM model (3) was employed, allowing fitting of the conductivity curves for each nanotube diameter independently.

Fig. 1 shows the result of modelling of the electrical conductivity of polymer nanocomposites based on polylactic acid and carbon nanotubes of different diameters, using GEM model. Fitting parameters of the modelling are shown in Table 2.

The fitting results demonstrate that the GEM model is capable of reproducing the general shape of the experimental curves, yielding high coefficients of determination (R^2 up to ~ 1.0 for some datasets). However, a detailed analysis of the obtained parameters reveals significant inconsistencies.

First, the critical exponent t, which is expected to be a universal parameter determined by the dimensionality of the system, exhibits strong variation across the datasets, ranging from approximately 1.3 to 4.3. Such variation cannot be justified within classical percolation theory and indicates that the model compensates for missing physical factors by adjusting the exponent.

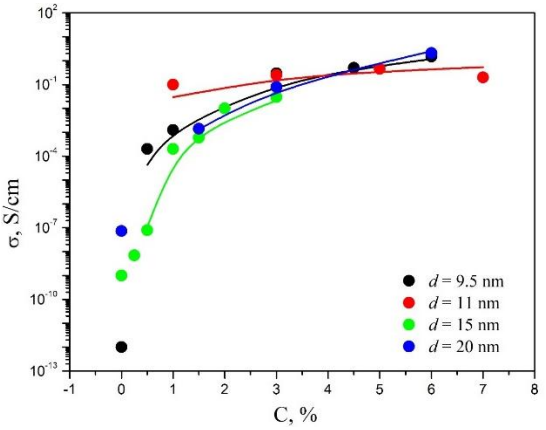


Fig. 1 – Modelling results of conductivity vs. CNT content (circles) using GEM model (solid lines)

Table 2 – Fitting parameters of GEM model

d, nm	σ_f, S/cm	t	C_c, %	R^2
9.5	$9 \cdot 10^{-3}$	3.2	0.25	0.90
11	$1 \cdot 10^{-1}$	1.3	0.5	0.85
15	$8 \cdot 10^{-4}$	4.1	0.35	0.92
20	$4 \cdot 10^{-5}$	4.3	0.5	0.92

Second, the effective conductivity of the filler phase varies by several orders of magnitude between different datasets, despite the fact that the similar type of carbon nanotubes was used. This indicates that the fitted parameters lose their physical meaning and become purely phenomenological.

These observations clearly demonstrate that, although the GEM model can approximate individual conductivity curves, it fails to provide a consistent and physically meaningful description of the system when the geometrical characteristics of the filler, such as nanotube diameter, are varied. The necessity to refit the model parameters for each dataset separately highlights its limited predictive capability.

In contrast, data-driven approaches, such as models based on artificial intelligence, are capable of capturing the multidimensional dependence $\sigma = f(C, d)$ within a single unified framework, without the need for parameter re-identification for each specific case. This makes them more suitable for describing complex nanocomposite systems where multiple interacting factors govern the electrical behavior.

3.2 AI-Based Model for Conductivity Prediction

A zero-order Takagi-Sugeno (TS) fuzzy model is characterized by a rule base in which the antecedent part consists of fuzzy conditions defined over input variables, while the consequent of each rule is represented by a constant value [22]. Each rule typically takes the form:

$$If\ x_1 \text{ is } A_1^i\ and \ldots\ and\ x_n \text{ is } A_n^i,\ then\ y = c_i, \tag{4}$$

where A^i_j are fuzzy sets and c_i are scalar constants. The core computational procedure involves several sequential operations: fuzzification of input variables using predefined membership functions, evaluation of rule firing strengths through t-norm operators (commonly product or minimum), aggregation of rule contributions, and final defuzzification via a weighted average mechanism [22]. Specifically, the model output is computed as a normalized weighted sum of the rule consequents, where the weights correspond to the firing strengths of the respective rules. This structure ensures computational simplicity, numerical stability, and efficient implementation, making zero-order TS models particularly suitable for problems with limited data and real-time processing requirements.

In this work, a synthesis and study of the effectiveness of the zero-order TS fuzzy-logical model was carried out, which allows reproducing the dependence of the electrical conductivity σ on the nanotube diameter D and the CNT concentration C at fixed values of other parameters, such as the degree of crystallinity and the manufacturing method.

In this model it is advisable to transform the output variable σ into a logarithmic scale (i.e., computing $\log_{10}\sigma$) due to its wide range, spanning multiple orders of magnitude (from 10^{-12} to 10^{0}), which helps mitigate skewness and heteroscedasticity, stabilize variance, and significantly improve the numerical conditioning and approximation accuracy of the model. When developing the model based on the above set of experimental data (Table 1), the following operating ranges were selected for each input and output variable: D – 9.5…20 nm; C – 0…7 %; $\log_{10}\sigma$– – 12…0.322. For the fuzzification of the input variable D, 4 linguistic terms (LT) were selected: VS – very small; S – small; M – medium; B – big. In turn, for the input variable C, 8 LTs were selected: Z – zero; VL – very low; L – low; BA – below average; A – average; AA – above average; H – high; VH – very high. Since the zero-order T-S mechanism for the output variables involves the use of clear numbers instead of fuzzy sets, in this case, 19 LTs in clear numerical form were selected for the output variable of the model $\log_{10}\sigma$: $mf_1 = -12$; $mf_2 = -3.699$; $mf_3 = -2.903$; $mf_4 = -0.523$; $mf_5 = -0.301$; $mf_6 = 0.176$; $mf_7 = -9$; $mf_8 = -1$; $mf_9 = -0.602$; $mf_{10} = -0.337$; $mf_{11} = -0.699$; $mf_{12} = -7.097$; $mf_{13} = -3.222$; $mf_{14} = -2$; $mf_{15} = -1.523$; $mf_{16} = -7.137$; $mf_{17} = -2.854$; $mf_{18} = -1.102$; $mf_{19} = 0.322$.

For all linguistic terms of the input variable D, 1st type Gaussian membership functions (MFs) were chosen. For the first six MFs of the variable C (Z, VL, L, BA, A, AA), also 1st type Gaussian MFs were chosen, and for the 7th and 8th (H, VH), 2nd type Gaussian MFs were selected. In turn, the 1st type Gaussian MF $\mu(D)$ for the variable D and the 2nd type Gaussian MF $\mu(C)$ for the variable C are described by expressions (5) and (6), respectively:

$$\mu(D) = e^{-\frac{(D-b)^2}{2a^2}}; \tag{5}$$

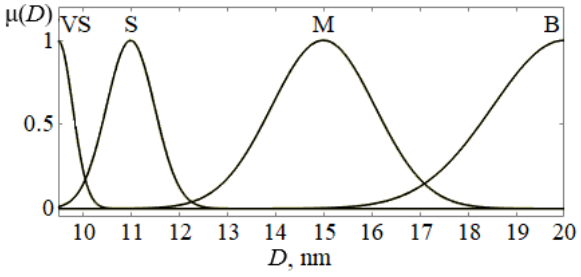
$$\mu(C) = \begin{cases} e^{-\frac{(C-b)^2}{2a^2}}, \text{ at } C < b; \\ 1, \text{at } b \le C \le d; \\ e^{-\frac{(C-d)^2}{2c^2}}, \text{at } C > d; \end{cases} \quad b < d, \tag{6}$$

where a, b, c, d – adjustable MF parameters.

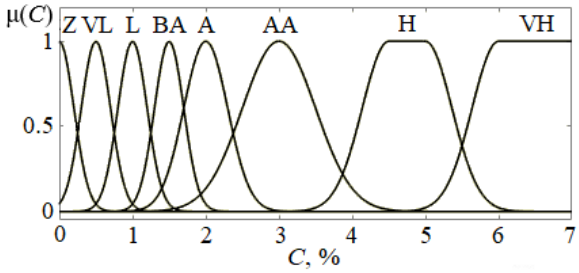
The appearance of the input variables' LTs with adjusted parameters of their MFs are presented in Fig. 2.

To connect the LTs of input (D, C) and output ($\log_{10}\sigma$) variables of the model in the form of antecedents and consequences of logical chains, a rule base (Table 3) was created, which allows reproducing the experimental dependences of these variables (Table 1) in a well-interpreted and intuitively understandable for a human form.

In particular, the constructed rule base consists of 21 rules, each of which has a consequent represented by a corresponding numerical term (presented above) of the output variable. Moreover, 19 different consequents are used in the 21 rules, since the 12th rule uses the term mf_7 and 14th rule uses the term mf_2.



a



b

Fig. 2 – Appearance of configured linguistic terms of input variables for the fuzzy model

Table 3 – Rule base of the fuzzy model

№	Rule
1	If (*D* is VS) and (*C* is Z) then ($\log_{10}\sigma$) is mf_1)
2	If (*D* is VS) and (*C* is VL) then ($\log_{10}\sigma$) is mf_2)
3	If (*D* is VS) and (*C* is L) then ($\log_{10}\sigma$) is mf_3)
4	If (*D* is VS) and (*C* is AA) then ($\log_{10}\sigma$) is mf_4)
5	If (*D* is VS) and (*C* is H) then ($\log_{10}\sigma$) is mf_5)
6	If (*D* is VS) and (*C* is VH) then ($\log_{10}\sigma$) is mf_6)
7	If (*D* is S) and (*C* is Z) then ($\log_{10}\sigma$) is mf_7)
8	If (*D* is S) and (*C* is L) then ($\log_{10}\sigma$) is mf_8)
9	If (*D* is S) and (*C* is AA) then ($\log_{10}\sigma$) is mf_9)
10	If (*D* is S) and (*C* is H) then ($\log_{10}\sigma$) is mf_{10})
11	If (*D* is S) and (*C* is VH) then ($\log_{10}\sigma$) is mf_{11})
12	If (*D* is M) and (*C* is Z) then ($\log_{10}\sigma$) is mf_7)
13	If (*D* is M) and (*C* is VL) then ($\log_{10}\sigma$) is mf_{12})
14	If (*D* is M) and (*C* is L) then ($\log_{10}\sigma$) is mf_2)
15	If (*D* is M) and (*C* is BA) then ($\log_{10}\sigma$) is mf_{13})
16	If (*D* is M) and (*C* is A) then ($\log_{10}\sigma$) is mf_{14})
17	If (*D* is M) and (*C* is AA) then ($\log_{10}\sigma$) is mf_{15})
18	If (*D* is B) and (*C* is Z) then ($\log_{10}\sigma$) is mf_{16})
19	If (*D* is B) and (*C* is BA) then ($\log_{10}\sigma$) is mf_{17})
20	If (*D* is B) and (*C* is AA) then ($\log_{10}\sigma$) is mf_{18})
21	If (*D* is B) and (*C* is VH) then ($\log_{10}\sigma$) is mf_{19})

The characteristic surface built on the basis of the developed TS fuzzy model is presented in Fig. 3.

The developed rule base and configured linguistic terms' parameters made it possible to achieve high accuracy of the AI-based model. The effectiveness of the TS fuzzy model used to predict the electrical conductivity for polylactide-CNT systems is shown in Fig. 4.

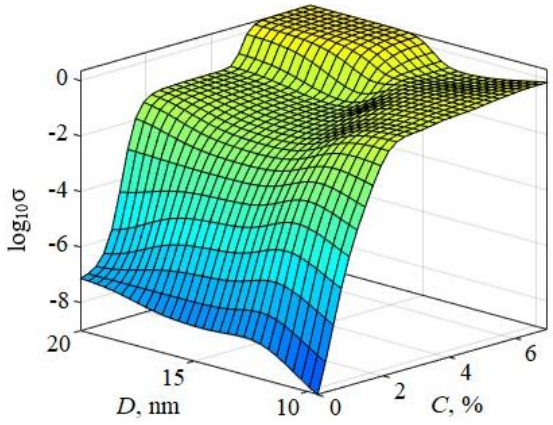


Fig. 3 – Characteristic surface of the developed TS fuzzy model

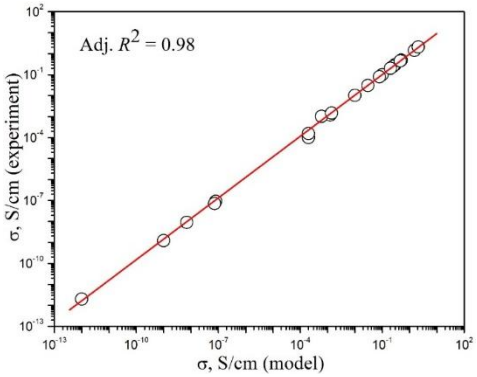


Fig. 4 – Comparison of the accuracy of predicted and experimental conductivity values obtained using the TS fuzzy model

The graph shows that the values of σ obtained using the model and from the experiment exhibit a linear correlation. The value of the coefficient of determination $R^2 = 0.98$, which is a very high indicator of predicting performance.

3.3 Physical Interpretation and Comparison of the Obtained Results

Analysis of three-dimensional surfaces of the dependence of electrical conductivity on the concentration and diameter of carbon nanotubes for polymer nanocomposites (Fig. 3) indicates a pronounced nonlinear nature of the change in the electrophysical properties of the system. The most characteristic feature is the presence of a sharp transition from the insulating to the conductive state upon reaching a certain critical content of nanotubes, which corresponds to the formation of a percolation structure in the material [24].

In the initial concentration range (up to ~ 0.5-1 wt. % CNT), the electrical conductivity remains extremely low and varies within several orders of magnitude (from ~ 10^{-12} to ~ 10^{-8} S/m depending on the diameter of the nanotubes). In this mode, charge transfer is carried out mainly due to electron tunneling between isolated filler particles through the polymer matrix [9]. The conductivity values in this region significantly depend on the diameter of the nanotubes: with an increase in diameter from 9.5 to 20 nm, an increase in the basic conductivity by several orders of magnitude is observed, which indicates a decrease in the effective barrier distance between the conductive elements and an increase in the probability of tunneling transport [25].

A sharp increase in electrical conductivity is observed in the concentration range of about 0.5-1.5 wt. % CNT, which corresponds to reaching the percolation threshold. In this interval, an infinite conductive cluster is formed, which provides effective charge transport through the material. The transition has the character of a jump-like change in conductivity by several orders of magnitude, which is in good agreement with the provisions of the percolation theory. In this case, the position of the threshold varies somewhat depending on the diameter of the nanotubes, but does not demonstrate a strictly monotonic dependence, which indicates the significant role of dispersion factors and interparticle interaction. In the post-percolation region (C > 1-2 wt. % CNT), a further increase in electrical conductivity is

observed, but at a slower rate. This is due to the densification of the conductive network and an increase in the number of contacts between nanotubes, which leads to a decrease in the total contact resistance. For all studied systems, at high concentrations (up to 6-7 wt. % CNT), the electrical conductivity reaches values of the order of 10^{-1}-10^{0} S/m, which indicates the formation of a well-developed conductive structure.

The influence of nanotube diameter on electrical conductivity is complex and multifactorial. On the one hand, an increase in diameter leads to an increase in conductivity in the pre-percolation region, which can be explained by a decrease in surface curvature and an increase in the effective contact area between nanotubes. On the other hand, in the post-percolation region, the dependence of conductivity on diameter becomes less pronounced, since the topology of the formed network begins to play a decisive role, rather than individual geometric characteristics of the particles.

Another result is that the Tagaki-Sugeno model allowed us to predict the behavior of electrical conductivity with increasing nanotube content and increasing their diameter. Fig. 3 shows a step-like change in electrical conductivity in this region. Such behavior may be a consequence of agglomeration of nanotubes, which combine into larger structures and form a percolation network of aggregates.

Thus, the electrical conductivity of polymer nanocomposites with carbon nanotubes is determined by the competition of two main mechanisms – tunneling charge transfer in the low concentration range and percolation transport after the formation of a continuous conductive network. The diameter of the nanotubes mainly affects the efficiency of interparticle contacts and tunneling parameters, which causes a change in electrical conductivity in the entire concentration range, but does not lead to a fundamental change in the nature of the dependence.

4. CONCLUSIONS

In this work, the electrical conductivity of polymer nanocomposites filled with carbon nanotubes was analyzed as a function of nanotube concentration and diameter. The conductivity behavior is governed by a transition from a tunneling-dominated regime at low filler content to a percolation-controlled transport mechanism at higher concentrations. While the general form of the conductivity–concentration dependence remains similar, the absolute conductivity values and the sharpness of the percolation transition are strongly affected by the nanotube diameter.

A comparison with classical analytical approaches, including percolation-based models and the McLachlan generalized effective medium model, showed that these methods can approximate individual conductivity curves but fail to provide a consistent description across systems with different nanotube diameters. The fitting parameters, such as the critical exponent and percolation threshold, exhibit significant variability and often lose their physical meaning, indicating that conventional models do not adequately account for the influence of filler geometry.

To address these limitations, a data-driven modeling approach based on fuzzy logic was used to develop a highly accurate predicting model. The proposed model enables the simultaneous consideration of multiple parameters without predefined functional relationships and provides a unified description of conductivity over the entire parameter space. The results demonstrate that artificial intelligence-based approaches, particularly fuzzy inference systems, are effective tools for modeling complex nanocomposite systems under conditions of limited data availability.

Overall, the study highlights the limitations of classical theoretical models and demonstrates the advantages of intelligent modeling techniques for predicting the properties of polymer nanocomposites. The proposed approach can be extended to other systems and used for the design of materials with tailored electrical characteristics.

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Прогнозування електропровідності полімерних нанокомпозитів із застосуванням нечітко-логічного підходу штучного інтелекту

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У роботі досліджено електропровідність полімерних нанокомпозитів, наповнених вуглецевими нанотрубками, з урахуванням впливу їх концентрації та діаметра. Експериментальні дані демонструють виражений нелінійний характер залежності електропровідності від вмісту наповнювача, що супроводжується переходом від тунельного механізму переносу заряду в області низьких концентрацій до перколяційного транспорту після формування безперервної провідної мережі. Показано, що діаметр нанотрубок істотно впливає на рівень електропровідності в усьому діапазоні концентрацій, зокрема в доперколяційній області, що пов'язано зі зміною ефективності міжчастинкових контактів та умов тунелювання. Проведено порівняльний аналіз експериментальних залежностей із використанням класичних аналітичних моделей, зокрема перколяційного підходу та узагальненої моделі ефективного середовища МакЛахлана. Встановлено, що ці моделі дозволяють описувати окремі криві електропровідності, однак їх параметри суттєво змінюються при зміні діаметра нанотрубок і втрачають фізичну інтерпретованість, що обмежує їх застосування для узагальненого опису системи.

Для подолання зазначених обмежень розроблено інтелектуальну модель електропровідності на основі нечіткої логіки, яка дозволяє одночасно враховувати концентрацію та діаметр нанотрубок без необхідності задання жорсткої аналітичної залежності. Запропонований підхід до моделювання забезпечує високу точність відтворення експериментальних даних і формує узагальнений опис залежності електропровідності від параметрів системи. Отримані результати підтверджують ефективність застосування методів штучного інтелекту для моделювання та прогнозування властивостей складних полімерних нанокомпозитів за умов обмеженого обсягу експериментальних даних.

Ключові слова: Полімолочна кислота, Полімерні нанокомпозити, Вуглецеві нанотрубки, Електропровідність, Штучний інтелект, Моделі нечіткої логіки.