Recent Advances in Machine Learning Research for Nanofluid-Based Heat Transfer in Renewable Energy System

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ABSTRACT: Nanofluids have gained significant popularity in the field of sustainable and renewable energy systems. The heat transfer capacity of the working fluid has a huge impact on the efficiency of the renewable energy system. The addition of a small amount of high thermal conductivity solid nanoparticles to a base fluid improves heat transfer. Even though a large amount of research data is available in the literature, some results are contradictory. Many influencing factors, as well as nonlinearity and refutations, make nanofluid research highly challenging and obstruct its potentially valuable uses. On the other hand, data-driven machine learning techniques would be very useful in nanofluid research for forecasting thermophysical features and heat transfer rate, identifying the most influential factors, and assessing the efficiencies of different renewable energy systems. The primary aim of this review study is to look at the features and applications of different machine learning techniques employed in the nanofluid-based renewable energy system, as well as to reveal new developments in machine learning research. A variety of modern machine learning algorithms for nanofluid-based heat transfer studies in renewable and sustainable energy systems are examined, along with their advantages and disadvantages. Artificial neural networks-based model prediction using contemporary commercial software is simple to develop and the most popular. The prognostic capacity may be further improved by combining a marine predator algorithm, genetic algorithm, swarm intelligence optimization, and other intelligent optimization approaches. In addition to the well-known neural networks and fuzzy- and gene-based machine learning techniques, newer ensemble machine learning techniques such as Boosted regression techniques, K-means, K-nearest neighbor (KNN), CatBoost, and XGBoost are gaining popularity due to their improved architectures and adaptabilities to diverse data types. The regularly used neural networks and fuzzy-based algorithms are mostly black-box methods, with the user having little or no understanding of how they function. This is the reason for concern, and ethical artificial intelligence is required.

1. INTRODUCTION

1.1. Background. The energy consumption and greenhouse gas (GHG) emissions in the world have been growing dramatically in recent decades because of the global population rise, as well as the sharply increased industry and transportation activities.[1,2] As illustrated in Figure 1, the global GHG emissions can be seen to roughly originate from four main categories, including energy, agriculture, industry, and waste.[3] However, energy consumption has been considered as the primary source of GHG emissions with around a 73.2% share,[4] showing that extensive use of fossil-based energy sources caused unfavorable impacts on the living environment because of the high level of GHG emissions.[5] Due to this reason, the development of renewable energies has been paid much attention in recent years due to their beneficial properties;[6,7] this could be observed more clearly during the post-COVID19 pandemic.[8]

In the development progress of energy systems, there has been a large interest in working fluids since they play a critical role in thermal efficiency and heat transfer capacity.[9,10] Due to their weak heat transfer characteristics, ethylene glycol (EG), water, and other common working fluids cannot provide sufficient heat transfer efficiencies in industrial operations. The ability of conventional fluids to transfer heat can be enhanced by suspending solid particles in them.[11] Over the years, researchers have focused their efforts on modifying heat transfer fluids using small-sized dispersed solid particles in the fluid. Indeed, using nanofluids could enhance the overall thermal efficiency significantly, and the total efficiency could be increased by 25% for nanofluids compared to the case of pure water.[12] However, these fluids experienced several issues,
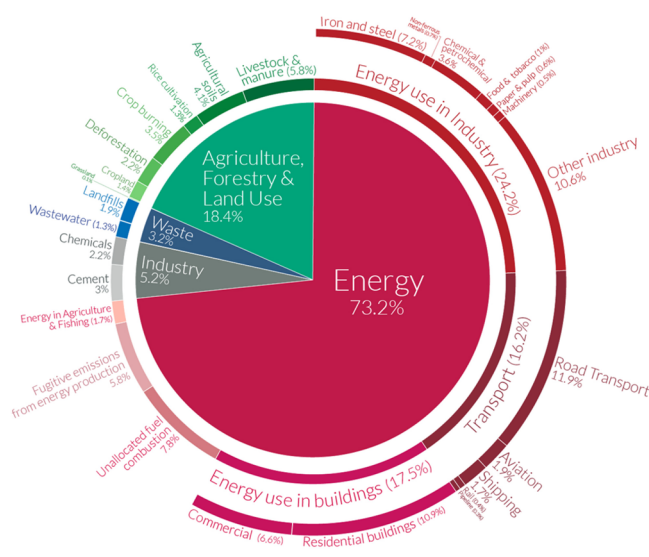
Figure 1. Global greenhouse gas emissions by sector[3] (reuse with permission of Elsevier via LN 5315110697148).

including particle swarming, channel blockage, transmission device degradation, increased pressure drop, and finally alluviation.[13] Particle settling reduced thermal conductivity and created sludge deposits, increased thermal resistance, and decreased the fluid's heat transfer capacity.[14] By 1881, James Clerk Maxwell had produced a significant revolution in heat transmission in fluids by introducing the notion of utilizing nanosized particles for the first time. He presented a new perspective on the liquid–solid suspension using nanosized particles. Okonkwo et al.[15] initially coined the term "nanofluid" to designate a fluid containing suspended particles, and Eshgarf et al. further refined the notion at the Argonne National Laboratory in the United States.[16]

These newer generations of heat transfer fluids, known as nanofluids (NFs), were invented based on this concept and breakthroughs in nanotechnology. The NFs are a blend of solid nanoscale materials (metal oxides, metals, nonmetals, and other nanoparticles) and a fluid known as the base fluid (like ethylene glycol, oil, or water).[17,18] NFs have emerged as a viable alternative to the currently utilized heat transfer fluids due to their superior heat transfer capabilities. NFs have better thermal conductivities and thermophysical characteristics.[19] That is why NFs are preferred for use in thermal management systems and heat transfer devices.[20] At present NFs are being used in solar collectors,[21] hydroelectric rotors,[22] geothermal heat exchangers,[23,24] wind turbines,[25] fuel cells,[26,27] chemical process plants,[28] and photovoltaic/thermal (PV/T) systems.[29,30]

The addition of nanosized particles to base fluids has a greater impact on the thermophysical characteristics of nanofluids. For example, in an experimental investigation by Moldoveanu et al.,[31] they used hybrid NF to enhance the thermal conductivity of NF by 19.2% in comparison with base fluid (water). Wole-Osho et al.[32] explored the effects of particle concentrations on the dynamic viscosity and specific heat of an Al_2O_3-ZnO-H_2O hybrid NF. In the case of the 2:1 ratio, viscosity is enhanced by 96.37%, while specific heat decreases by 30.12% at 25 °C temperature. Xian et al.[33] explored the influences of ultrasonication time and a variety of surfactants on the thermophysical properties of NFs. The experimental study used a hybrid NF of graphene nanoplatelets

with titanium dioxide. The nanoparticles were dispersed in a mixture of EG and water. It was experienced that the thermal conductivity was enhanced up to 23.74%. Kakavandi and Akbari[34] reported an enhancement of thermal conductivity up to 33% with hybrid NFs−binary base fluids (MWCNTs-SiC/ Water-EG). Several other studies reported the impacts of hybrid NFs in improving thermophysical properties to make heat transfer fluids more suitable for energy systems.[35−38] In recent years, a novel class of working fluids has been identified and actively investigated, consisting of three solid nanoparticles scattered in a typical fluid. These fluids are known as ternary nanofluids, ternary hybrid nanofluids, or trihybrid nano-fluids.[39,40]

Nanofluids are utilized in sophisticated heat exchange processes and energy systems due to their better thermophysical properties than base fluids. They have nonlinear impacts on fluid flow, heat transfer, optics, stability, and radiative performances. Mapping their effects on complex thermal processes and the effects of different mixing ratios is cumbersome.[41] As a result, artificial intelligence-based machine learning (ML) might be used in nanofluids research. The advent of improved computational facilities with advanced machine learning algorithms has made it possible to predict the thermophysical properties of hybrid NFs.[42]

1.2. Renewable Energy. Energy is critical to industrialization, economic progress, education, and urbanization in today's world. As per the US EIA briefing, worldwide energy consumption is increasing at a rate of about 2.3% each year. According to the report, petroleum will be in limited supply throughout the planet shortly.[43] Fossil fuels are also a major source of environmental contamination, such as air and water pollutions. As a result, renewable sources of energy such as biomass, solar, geothermal, wind, and others have received considerable attention as prospective energy development options.[44,45] Environmental limitations are frequently violated in the existing global energy system. The basic energy requirements are not fulfilled for the masses, and energy justice is not guaranteed for everyone. In essence, the energy system is unsustainable, and it is on a path to stay unsustainable in the future. This realization spurred the United Nations to establish 17 sustainable development goals (SDGs), one of which (SDG 7) envisions a future where everyone has access to cheap, dependable, sustainable, and modern energy services by 2030.[46,47] SDG 7 is not the only goal for which sustainable energy is important. The development of renewable, clean, and sustainable energy sources is important to attaining the United Nations' sustainable development goals (SDGs),[48] even though developing energy systems with renewable sources is the first step toward achieving global environmental sustainability in many industrialized economies.

The studies in the past point out that meeting the global energy demands sustainably has been a critical concern for humanity.[49] As a result, to maximize their sustainability, optimal design, and economic viability, a thorough understanding of sustainable energy systems is required. Sustainable energy systems have previously been characterized as explicit domains that employ energy sources projected to decline in a time frame relevant to the human race. Significant research efforts have been undertaken to enhance renewable energy generation to meet the global target of reducing energy consumption and CO_2 emissions by 20% by the year 2030.[50] Furthermore, the massive rise in energy consumption in recent

years as a result of fast industrial development and population expansion confirms that developing renewable, clean, and sustainable energy source Research Center in Systems Ecology and Sustainability (RCSES) is now a key priority in many nations across the world,[51] as seen from the creation of the Research Center in Systems Ecology and Sustainability (RCSES). As a result, not only RCSES are developed for achieving SDGs but also their behaviors and performances under various operating situations must be understood.

Figure 2 illustrates the statistics on the number of published research articles on nanofluids (NF), machine learning (ML),
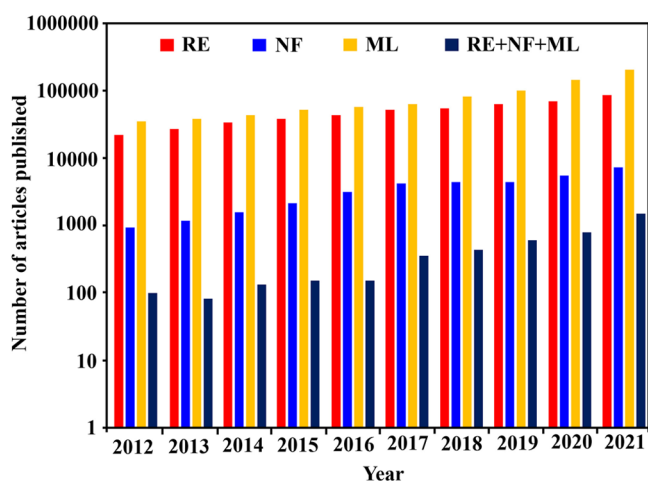

Figure 2. Number of research articles published in renewable energy, nanofluids, machine learning, and their combinations.

and renewable energy (RE) and also a combination of these three domains obtained from keyword searches on the Web of Science on February 3, 2022, for the decade 2012−2021. The data on NF came from a subject search with the key phrases "nanofluid" or "nanofluids". The analysis data on ML came from a variety of searches that included the terms "adaptive neuro-fuzzy", "artificial neural network", "category and regression tree", "artificial intelligence", "support vector machine", and "random forest". The data of published articles on renewable energy were searched using the terms "renewable" and "renewables". The graph shows that publications in these areas have grown considerably in recent years, with renewable energy having the most articles, followed by machine learning and nanofluids. However, nanofluid publications utilizing machine learning in the renewable energy domain (i.e., a combination of these three search queries) are scarce, gradually increasing from a two-digit yearly figure in the period 2012−2013 to approximately 1468 in 2021, accounting for approximately 1.7% of renewable energy research publications in that year. As a result, the nanofluid research community must focus more on machine learning research in the renewable energy sector.

1.3. Novelty of the Review Study. Machine learning technologies based on AI are being utilized to model business and engineering difficulties in virtually every industry. Most energy-producing industries in the renewable energy arena use some form of heat transfer. Numerous research studies indicate the efficacy of nanofluids in boosting the heat transfer rate. The selection of an acceptable nanofluid for a specific renewable energy application, on the other hand, is a crucial challenge. The selection of a suitable nanofluid is based on an assessment

of its thermophysical properties via a thorough characterization technique.[52] The repeated comprehensive characterization of multiple nanofluids is time consuming and labor intensive and requires a significant investment in specialized testing equipment and raw materials.[53] Machine learning approaches are a viable answers to these challenges in nanofluid characterization. Modern machine learning algorithms can effectively construct a prediction model from experimental data, which may then be used to predict features in future investigations. Table 1 highlights key review articles published in the previous five years on the use of machine learning techniques in the use of nanofluids in the renewable energy field.

Table 1. Summary of Review Papers on Use of Machine Learning Techniques for Utilization of Nanofluids in Renewable Energy Domain in Last Five Years

Reference	Focus area	Year
Akhter et al.[54]	Application of machine learning in photovoltaic power generation	2019
Mosavi et al.[55]	Applications of machine learning system in general energy systems	2019
Ramezanizadeh et al.[56]	Utilization of machine learning for estimation of nanofluid dynamic viscosity	2019
Diogo et al.[57]	Machine learning for energy efficiency in industry	2020
Shateri et al.[58]	Machine learning for nanofluid viscosity estimations	2020
Antonopoulos et al.[59]	Artificial intelligence in demand-side response of energy	2020
Fathi et al.[60]	Machine learning in performance forecasting of urban building	2020
Ahmad et al.[61]	Artificial intelligence in sustainable industry	2021
Ma et al.[62]	Nanofluids heat transfer applied to renewable energy	2021
Jamei et al.[63]	Evaluations of data analysis techniques for estimations of nanofluid specific heat	2021
Aghbhaslo et al.[64]	Machine learning techniques for biodiesel research	2021
Hoang et al.[65]	Artificial neural network for behaviors of diesel engine fueled with biodiesel	2021
Wang et al.[66]	Machine learning methods applied for use of nanofluid in a heat pipe	2021
Adun et al.[67]	Evaluations of machine learning techniques for forecasting of nanofluid specific heat	2021

An examination of review articles published in the previous five years (2017−2022) revealed that while numerous review studies on the thermophysical properties of nanofluids are available in the open literature only a few on the use of nanofluids in conventional energy systems or demand forecasting are available. Even though machine learning methods are rapidly being employed in nanofluids and renewable energy, no comprehensive research evaluation on machine learning applications in nanofluid-based renewable energy systems exists. The present work seeks to connect the dots to provide a comprehensive analysis of the connected research domains of machine learning, nanofluids, and renewable energy. In Section 2, the review article outlines the approach used throughout the review of the relevant literature. Section 3 provides a detailed analysis of different machine learning approaches, while Section 4 provides a detailed examination of the use of machine learning techniques for modeling and forecasting thermophysical characteristics of

nanofluids. Section 6 discusses the use of machine learning approaches in the field of renewable energy. Section 7 discusses the problems and opportunities of employing machine learning techniques in nanofluid-based renewable energy systems, followed by the study's key findings.

2. METHODOLOGY

The present study examines the most recent research on the use of machine learning methods in nanofluid heat transfer. Over the past decade, there has been a surge in research papers on the use of machine learning methods.[68−71] In the past, a variety of machine learning approaches have been employed to model and forecast the properties of nanofluids.[41,68,72] With the advent of newer machine learning methods, the ever-increasing computational power is the catalyst for the increasing popularity of machine learning techniques.[73,74] As a result, the current study attempts to compile a comprehensive report including the most recent developments in this subject for easy reference. Because these strategies are constantly changing, examining and portraying just the most recent work is critical. As a result, the research papers over the past three years were examined and a few notable works from prior years. The study's data was gathered from Scopus, Google Scholar, Web of Science, and the Google search engine. Journals referred to included *Journal of Cleaner Production, Energy & Fuels, Energy Conversion and Management, Renewable and Sustainable Energy Reviews, Energy, Powder Technology, Journal of Molecular Liquids, International Journal of Heat and Mass Transfer, Fuel,* and *Journal of Thermal Analysis and Calorimetry.* The research studies published in the field of machine learning-based model prediction of engineering applications were examined. The research papers were divided into categories using machine learning methods. Each approach's efficacy was then evaluated in terms of model prediction quality. The subsequent phase investigated the machine learning methodologies utilized for model prediction of thermophysical properties of nanofluids. The literature on a comparative analysis of several machine learning methodologies was beneficial in deciding which techniques were best suited to the nanofluid domain. The methodologies used in machine learning to develop prognostic models for thermal conductivity, density, specific heat, and viscosity were examined. The study was broadened to include the use of machine learning methods for renewable energy sources to present a more complete picture for future researchers.

3. MOST RELEVANT MACHINE LEARNING TECHNIQUES

3.1. Multilayer Perceptron Artificial Neural Network.

Two types of studies, experimental and analytical, are utilized to assess the performance of engineering systems in the research field. As the process of achieving satisfactory results may necessitate multiple lab-based trials, the experimental studies become more expensive as they need extended manhours, material resources, and energy.[75,76] Most engineering systems are becoming more complex with time, so mathematical modeling with the first principle is increasingly becoming complex. Soft computing techniques are useful in this domain to save costs.[77] In the field of artificial intelligence, the artificial neural network (ANN) is a useful technique for model prediction, because it saves time and yields more precise findings than other approaches.[78,79] The ANN technique has

risen in popularity in the engineering and energy industries during the past decade. ANN is a simple, easy-to-use, fast computing technique capable of solving complex nonlinear problems.[56,80,81] The only drawback is the correct design of the network and the requirement of a larger data set for modeling.

The most fundamental neural network architecture is the multilayer perceptron (MLP). Because all neurons in each layer have forward connections to all neurons in the layer above, it is also known as a feed-forward neural network. As illustrated in Figure 3, the MLP-ANN approach comprises
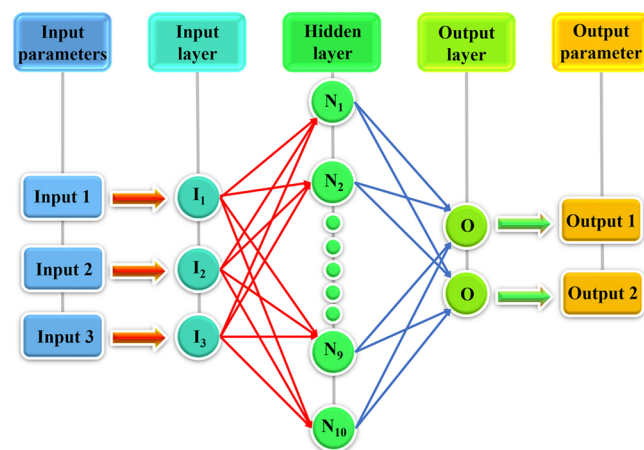

Figure 3. Line diagram depicting MLP-ANN.

three layers: the first input layer, which is used to get input data; certain interlayers known as hidden layers; and the final layer, or output layer, which reveals the ANN's projected outcomes. Every node is allotted a weight vector to link with the following layers' nodes. Every node present in the MLP-ANN model can receive inputs, process them, and provide an output.[56,68] In a combined form, the input layer's nodes act as input for the next (hidden) layer's nodes. In general, this method attempts to iterate ML on time series and nonlinear data like that of the human brain. Assume that the input vector is "X" such that

$$X = [x_1, x_2, x_3, x_4, \cdots\cdots, x_n]^K \tag{1}$$

If n_j is taken as the input for the jth node in the middle layer (hidden), then

$$n_j = \sum_{i=1}^{n} \omega_{ij} x_i + j, \quad \text{where } j = 1, 2, 3, \cdots, T \tag{2}$$

$$y_j = f(n_j) = f\left(\sum_{i=1}^{n} \omega_{ij} x_i + \theta_j\right), \text{where } j = 1, 2, 3, \cdots, T \tag{3}$$

where K, ω_{ij}, and f denote the node indexing in the hidden layer, weight between the ith input node and jth output node, and the transfer function, respectively.

Each function has its own set of features and may be used in a variety of different engineering problems. The output node is formed by multiplying the output of every hidden node by the output linking weight of that node. The counts of hidden neurons in the input and output layers in the MLP-ANN model are governed by the number of variables in the examined application. However, there is no proven approach

for estimating the number or sizes of hidden layers.[82,83] The number of hidden layers can be modified depending on the scale of the problem, the quality, and the quantity of data. As a result, neurons are regularly adjusted depending on iterations during the training to achieve the optimal amount.[84,85] The construction of a predictive MLP-ANN model necessitates the establishment of a training stage. When multiple input and output groups are supplied to build a network, the prediction process regulates weight and bias values. Backpropagation (BP) is a training method widely used in the training mode of MLP-ANNs to manage bias and weight values.[86,87]

3.2. Adaptive Neuro-Fuzzy Inference System.

The term "neuro-fuzzy" refers to a hybrid artificial intelligence approach that blends fuzzy logic and artificial neural networks. In ANFIS, the learning capability and relational architecture of artificial neural networks are combined with the logical process of fuzzy logic.[88] ANFIS, like artificial neural networks, may be trained with a large amount of data. As a consequence, the best optimum ANFIS structure for solving the related issue is discovered.[89] The resultant ANFIS architecture is tested to observe how it reacts to new samples. The ANFIS network topology is divided into two components, referred to as the premise and effect parts. ANFIS training entails using an optimization method to determine the parameters associated with these components. During training, ANFIS takes advantage of the existing control and response variables data pairings. Following that, fuzzy IF−THEN rules are built to demonstrate that these portions are linked.[52,90]

The fuzzy inference systems (FIS) are also referred to as fuzzy models, fuzzy rule systems, fuzzy controllers, or fuzzy associative memory in literature. A FIS is made up of five functional parts: a rule base that comprises multiple fuzzy if−then rules and also a database that specifies the membership functions of a processing unit that conducts the inference, combined with a unit that performs the inference. This is followed by a fuzzification interface that converts crisp inputs into fuzzy inputs and a defuzzification stage that transforms fuzzy inputs into crisp output. The knowledge base is usually referred to as a combination of the rule base and the database.

ANFIS is made up of five layers, as shown in Figure 4. ANFIS architecture with two numbers of inputs and a single
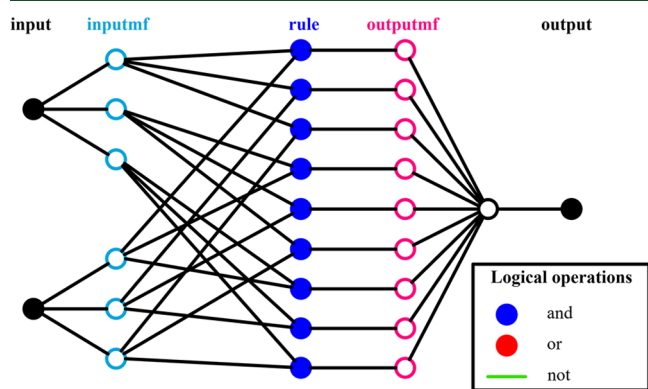

Figure 4. Typical ANFIS structure.

output is shown in this diagram. As per the ANFIS structure illustrated in Figure 3, the first layer is referred to as the fuzzification layer. To generate fuzzy clusters from input data, the fuzzification layer employs membership functions. The premise parameter is a set of parameters that governs the shape

of the membership function. The premise parameter set is a, b, and c. As listed in eqs 4 and 5, these parameters are used to determine the membership degrees of each membership function.[91] The membership degrees are shown with θ_x and θ_y as

$$\theta_{A_i}(x) = \frac{1}{1 + \left| \frac{x-c}{a} \right|^{2b}} \tag{4}$$

$$O_i^1 = \theta_{A_i}(x) \tag{5}$$

The second layer is referred to as the rule layer. Membership values obtained in the fuzzification layer are used to produce firing strengths (ϕ_{ii}) for the rules. The membership values are multiplied to find the ϕ_i values, as shown in eq 6. The third layer is denoted as the normalizing layer. It also determines each rule's normalized firing strengths. The normalized value is the firing power ratio of the ith rule to the total of all firing strengths, as determined by eq 7. Defuzzification is the name of the fourth layer. In each node of this layer, weighted values of rules are determined as shown in eq 8. The value is calculated using a first-order polynomial.[92,93]

$$O_i^2 = \varphi_i = \theta_{A_i}(x) \cdot \theta_{B_i}(y), \text{ where } i = 1, 2 \tag{6}$$

$$O_i^3 = \overline{\varphi_i} = \frac{\varphi_i}{\varphi_1 + \varphi_2 + \varphi_3 + \varphi_i}, \text{ where } i = 1, 2, 3, 4 \tag{7}$$

$$O_i^4 = \overline{\varphi_i} f_i = \overline{\varphi_i}(p_i x + q_i x + r_i) \tag{8}$$

$$O_i^5 = \sum_i \overline{\varphi_i} f = \frac{\sum_i \varphi f_i}{\sum_i \varphi_i} \tag{9}$$

The actual ANFIS result is achieved through the last (fifth) layer. This layer is known as the layer of summation. The total outcome is calculated by adding the results of the respective rule inside the defuzzification layer. Equation 9 denotes the ruling expression for this layer.

3.3. Gene Expression Programming.

GEP is an established algorithm that uses computer program evolution to solve linear and linear engineering problems. The computer program in GEP is generally encoded by fixed-length gene expression strings that are developed using nature-inspired operators like mutation and crossover. GEP has been proven to help find a precise and concise computer-based model for output prediction. Time-series predictions, classification difficulties, regression issues, data mining, and knowledge discovery are just a few of the real-world applications where it has been used with great success. It uses the historical data set of the problem to offer a solution in the form of an expression tree (ET). Ferreira[94] created this approach in 1999, and it was publicly launched in 2001. The GEP algorithm combines the major views of the two earlier legacy algorithms, namely, genetic programming (GP) and genetic algorithm (GA), to solve their flaws. In this technique, the chromosomal genotype is similar to that of a GA, whereas the phenotypic of a chromosome is a tree data structure of varying length and size, comparable with that of the GP algorithm.

In the case of several variables, the logical link between them (if any) may be a function of at least a function that can be correctly stated. The linking function can be Boolean logic operators (like IF, OR, and AND) and/or arithmetical operators (+, −, ×, /) or algebraic functions like exponential

and trigonometric. The logical link between variables should, of course, be investigated. Generally, three ETs are formed during the model development, and the sum of these form the overall model. A typical example of ET[73] is shown in Figure 5. Utilizing the GEP technique, a group of linear type chromosomes is initially generated to discover the connection between variables a and b and y.
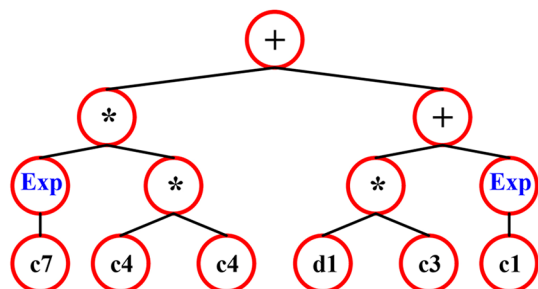

Figure 5. Typical expression tree.

One of the variables may be inserted at each location of the genes on these chromosomes. It is time to evaluate each person's fitness (chromosome) in the generation examined once the chromosomes have been produced and their places filled. The chromosomes are represented as an expression tree in the GEP method for this reason (ET). An ET is comparable to a protein found in natural cells that controls the phenotype of a gene.

The conventional GEP technique consists of several operations. The first one is an initialization to create the starting population by producing a set of random chromosomes. Each element of the fixed-length strings is randomly assigned to each chromosome in the initial population based on the element's type. Functions and terminals are allocated to elements belonging to the head portion, whereas terminals are assigned to elements belonging to the tail component. The next operation is the fitness assessment, in which the fitness strengths of all chromosomes in the population are assessed. The problem-specific fitness evaluation function has a noteworthy impact on the performance of the test algorithm. The next stage is selection and replication. This stage selects the population's better chromosomes to create a new group for the upcoming generation. The roulette-wheel selection method and the tournament selection strategy are two examples of selection strategies that can be employed. The roulette-wheel selection with elitism has been demonstrated to produce superior results when tackling complicated issues.

3.4. Least Square Support Vector Machine (LS-SVM). Cortes et al.[77] originally proposed the support vector machine (abbreviated as SVM) in 1995. To overcome the problematic linear indivisibility, it employs the kernel function and follows Mercer's theorem to abstract features from the source. It has a strong capacity for generalization and can handle real issues such as minuscule samples, nonlinear data, and handling of local minima.[87,95] It does, however, have the restricted quadratic programming problem, which has a significant calculation complexity. A generalized flowchart of LS-SVM is shown in Figure 6.

The support vector machines (SVM) offer higher generality than other machine learning approaches, so the SVM has gained substantial attention in the past decade as a strong prognostic tool. SVM technology is used in a variety of
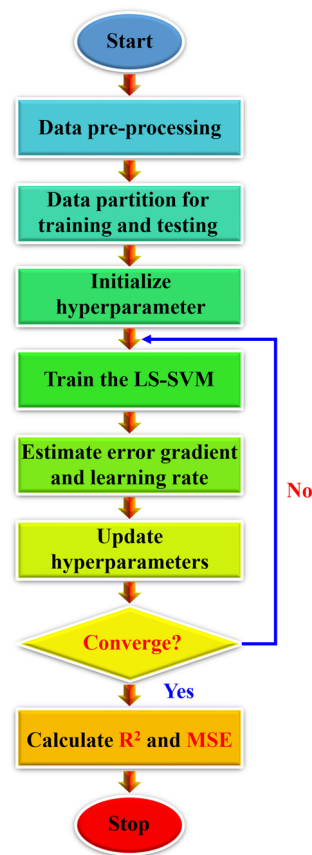

Figure 6. Flowchart of LS-SVM process.

industries due to its strong generalization abilities like face identification, feature selection, and function estimation.[79] The expanded model of conventional SVM, least squares SVM (LS-SVM), transforms a quadratic programming (QP) problem into linear equations.[96] It is possible to achieve both a fast solution speed and a stable real-time function with this method. If $T = \{(x_i, y_i)\}$, where $(i = 1, 2, 3, \ldots, N)$, T denotes training data, x_i the measured value and y_i the predicted value. Then, LS-VSM can be expressed as

$$y(x) = \omega^T \mu(x_i) + d + e_i \tag{10}$$

In eq 10, ω denotes the assigned weight vector, $\mu(x_i)$ a nonlinear function, d deviation, and e_i residuals in the fitting.

$$\text{Also, Min } F(\omega, e) = \frac{1}{2}\omega^T\omega(x_i) + \gamma\frac{1}{2}\sum_{i=1}^{n} e_i^2 \tag{11}$$

$$\text{If } y_i = \omega^T \mu(x_i) + d + e_i, \text{ and } i = 1, 2, 3, \cdots, N \tag{12}$$

This describes Lagrange function L such that

$$L(\omega, b, e, \sigma) = I(\omega, e) - \sum_{i=1}^{n} \sigma_i\{\omega^T\mu(x_i) + d + e_i - y_i\} \tag{13}$$

In eq 13, the Lagrange multiplier is denoted with σ_i, in which the partial derivatives of ω, b, e, are achieved at a point where σ_i becomes 0 to attain the optimization condition. At the optimized condition, ω is removed, and regression is accomplished.[77]

$$y(x) = \sum_{i=1}^{n} \sigma J(x, x_i) + b \tag{14}$$

The LSSVM model for prediction is developed using the following steps:

(i) Normalize the experimental data, and split it into two categories: training data and prediction data.

(ii) The crossover technique is used to search the LS-SVM parameters using the training data, the specified kernel function, and the multiclass coding scheme.

(iii) Finally, the prognostic model is developed with LS-SVM parameters.

3.5. Other Novel AI Methods. Traditional ANN seeks to construct a straight mapping between historical input data and output prediction data to achieve the forecasting method. However, the ANN-based model cannot characterize the link between data and time because of the absence of consideration of the time correlation in the data sequence, limiting its usefulness in time series forecasting techniques.[97] Therefore, the recurrent neural network (RNN) is offered as a solution to this problem. RNN may build a sequential mapping between input and output data by establishing cyclical connections to neurons. Thus, the output of each time step is influenced by the preceding time step's input. As a result, RNN realizes the "memory" feature.[98]

A backward and forward are included in the RNN training procedure. The forward pass of an RNN is like a single hidden layer of a MLP. The stimulations from both the current external input and previous time steps' hidden layer responses appear at the hidden layer.[99] The nuance is that the loss function for RNN is affected by the instigation of the hidden layer not only via its effect on the output layer but also by its impact on the hidden layer at the subsequent step.[98] Hochreiter and Schmidhuber[100] proposed the long short-term memory (LSTM) network in 1997, a kind of RNN that integrates learning and model training without the need for extra domain knowledge. In contrast to traditional RNNs, the enhanced LSTM structure helps to minimize gradient collapse and explosion. As a result, LSTM has benefits in capturing long-term dependency and modeling nonlinear dynamics, and it may be utilized to cope with lengthy sequence data.[98,101]

The radial basis function (RBF) neural network is also widely used because of its advantages, which include a simple structure, more estimation features, and a rapid training algorithm. The RBF network is a powerful conventional neural network structure.[102] RBF networks are made up of three layers. The input layer's sole purpose is to link the network to its surroundings. The hidden layer comprises several nodes that use a radial basis function, such as the Gaussian function or the thin plate spline function, to apply a nonlinear modification to the input variables. The output layer is a summation unit and is linear.[103]

The structure of an RBF network is selected through trial and error in the standard training method. The network parameters are determined in two stages. On the basis of the k-means clustering method, the centers of the hidden layer nodes are determined in the first. The connection weights are generated in the second step using basic linear regression.[104,105] Researchers in classification and model prediction also apply modern machine learning methods such as XGBoost, CatBoost, Boosting, Bagging regression tree, and LightGBM. In nanofluid-based heat transfer applications, the machine learning methods discussed in the previous subsections were mainly reported in the literature. To enhance prediction accuracy and computing efficiency, such machine learning approaches can be coupled with genetic algorithms, particle swarm optimization, and imperialist competitive algorithm.[106] The important historical progress in machine learning application in the domain of nanofluids is shown in Figure 7.
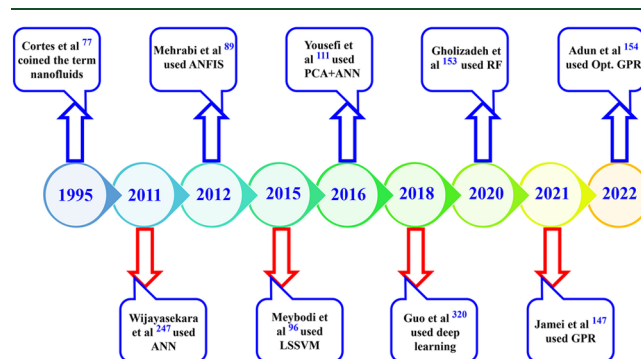

Figure 7. Flowchart of important previous research on a time scale.

3.6. Overfitting Problems in Machine Learning-Based Prediction Models. Although machine learning algorithms are adaptable to the properties of the observable values, overcomplexity in such models might result in overfitting. Overfitting occurs when the predicting algorithm describes the in-sample data too well, integrating not only the information associated with the data process but also the noises particular to that sample. In this scenario, the model is simply "memorizing" the observed patterns from the history, and thus, it is not truly "learning" the relevant patterns.[107,108,109]

As previously stated, one of the causes of overfitting is that input signals are mixed with noises, resulting in poor accuracy; thus, increasing the data size is one method by which we can avoid the mixing of signals and noises. In machine learning, limiting the iteration is also known as the "early halting" approach; this overfitting avoidance strategy works only when our machine learning model learns repeatedly. Another method for improving the model's accuracy is to merge all of the weak learners into strong learners. This may be accomplished by bagging and/or boosting.[79,110] Cross-validation is another machine learning approach that gives a solution to the overfitting problem. Cross-validation, like ensemble learning, splits the data set, but the process is different. Regularization is another effective and widely used machine learning strategy for avoiding overfitting; this method matches the function of the training data set. This procedure causes the coefficient to move toward zero, minimizing mistakes.

3.7. Evaluation and Validation of Models. The precise uses of model assessment, model evaluation, and algorithm selection approaches are crucial in the efficient usage of machine learning techniques.[111] The main techniques for model evaluation and selection include the holdout method if the data set is small. The bootstrapping procedure is better suited for a larger data set. The bootstrapping technique is a resampling process for calculating population statistics by sampling a data set with replacement. It may be used to produce summary statistics like mean and standard deviation. Cross-validation and hyperparameter adjustment are other

computationally feasible strategies for model assessments. Common cross-validation procedures such as leave-one-out cross-validation and k-fold cross-validation have been employed by machine learning researchers.[112,113]

Statistical assessment is one of the most common approaches for the evaluation of the prognostic efficacy of the models. The general indicators such as coefficient of determination, coefficient of regression, mean squared error, mean absolute percentage error, and Theil's statistics have been utilized by various published investigations.[114] The appeal of statistical approaches for regression issues arises from their simplicity of implementation and flexibility irrespective of the size of the data set. Finally, when comparing machine learning algorithms with limited data sets, additional algorithm selection procedures such as the combined F-test, 5 × 2 cross-validation, and nested cross-validation are also advocated.[115]

4. MACHINE LEARNING FOR THERMOPHYSICAL PROPERTIES

The heat transfer in a heat exchanger device or equipment is dependent on the characteristics of the heat transfer fluid; therefore, precise measurement and forecasting of nanofluid's thermophysical characteristics are important.[116] However, numerous factors impact the thermophysical characteristics of a nanofluid, including nanoparticle type, concentration, shape, size, shape, temperature, rate of shear, preparation method, kind of base fluid, flow condition, and so on. For example, hundreds of high thermal conductivity nanoparticles, such as Al_2O_3,[81] Ag,[117] CuO,[118] graphene,[19] SiO_2,[18] MgO,[117] Ni,[119] TiO_2,[120] Fe_3O_4,[121] and SiC[122], have been investigated for producing nanofluids. As a result, determining the thermophysical characteristics of a nanofluid is exceedingly difficult and remains a key challenge in nanofluid research. Experimental property measurement costs are high, and the parametric data range is limited.[62] Analytical or numerical models need values of different nanofluid properties and interactions between nanoparticles and base fluids to be understood. On the other hand, machine learning is capable of reducing in several experimental studies. Once the prognostic model is developed, it can be used for forecasting the thermophysical properties with high accuracy.

4.1. Thermal Conductivity. The basic aim of developing nanofluids was to enhance the thermal conductivity of the base fluid by adding nanoparticles. A significant number of experimental studies have been carried out to test the thermal conductivity of nanofluids during the last two decades using various technologies such as the temperature oscillation method, transient hot-wire method, and steady-state parallel plate method. The thermal conductivity of a test nanofluid is determined by numerous parameters, including nanoparticle size, concentration, synthesis technique, and temperature. The majority of the literature revealed that nanofluids might increase heat conductivity to various degrees.[123,124] The basic characteristics of nanoparticles, base fluid, and their temperature, are macroscopic parameters that can impact the thermal conductivities of nanofluids.[125]

One of the most significant factors for theoretical as well as numerical analyses of heat transport systems employing nanofluids as coolants is the selection of nanofluid's thermophysical characteristics. Given this, understanding how to create an appropriate thermophysical characteristic model is quite beneficial and important. The analytical model-based

method and data-driven machine learning approach are the two main approaches used to model and forecast the characteristics of nanofluids.[62,126] Compared to the analytical model-based method, the data-driven machine learning approaches represented by the ANN,[42,127] ANFIS,[128] GEP,[129] for example, have attracted a lot of interest in recent years because of their superior mapping, modeling, and forecast capabilities. According to the literature study, the predictive models' accuracies are related to their structures, functions used, input variables used, and algorithms used.[66,68] Maleki et al.[130] conducted a comparison of prediction performances for three machine learning algorithms For model prediction of the TC of nanofluids containing ZnO nanoparticles, the multivariate adaptive regression splines (MARS), ANN, and group method of data handling (GMDH) were utilized. To compare the models' confidences, several statistical indicators were utilized. The most accurate model has been determined to be ANN, followed by GMDH and MARS. ANN, GMDH, and MARS had R^2 values of 0.998, 0.998, and 0.987, respectively. The sensitivity analysis found that the thermal conductivity of the base fluid was the most critical input component. The thermal conductivities of nanofluids containing CuO nanoparticles were model predicted by Komeilibirjandi et al.,[131] using ANN and GMDH. Both models employed thermal conductivities, temperature, mass fraction, and nanoparticle size as inputs. When polynomial and ANN were utilized, the R-squared values were 0.986 and 0.9995, respectively. On the basis of these statistical findings, it is possible to conclude that utilizing an ANN-based regression to predict the TC of nanofluids containing CuO nanoparticles produces a more trustworthy model. Rostami et al.[132] explored the effects of adding MWCNT on the TC of paraffin using a comparative study between ANN and the response surface methodology (RSM). A nanofluid temperature (25−70 °C) and mass fraction (0.005−5%) were used as input variables, while the nanofluid thermal conductivity was used as an output parameter. Finally, both methods' mean squared errors (MSEs), R, and maximum margin of deviation (MMD) were compared. The R indices for ANN and RSM models were 0.993 and 0.972, correspondingly, implying that the ANN approach was more accurate than the RSM. Maleki et al.[133] applied GMDH, ANN with scaled conjugate gradient (SCG), and the Levenberg−Marquardt (LM) training algorithm for prediction of thermal conductivity of silica nanoparticles in different base fluids. The model-based prediction results were quite close to the results of experimental research. The R^2 values for GMDH, LM, and SCG in optimal circumstances were 0.9996, 0.9990, and 0.9998, individually. Furthermore, the MSE using these three techniques were 0.000010, 0.000032, and 0.0000078 for GMDH, LM, and SCG, respectively.

In a study by Alrashed et al.,[134] carboxylic diamond nanoparticles and multiwalled carbon nanotubes were dispersed in water without the use of any chemicals or surfactants. The viscosities, thermal conductivities, and densities of the nanofluids were then measured at temperatures ranging from 20 to 50 °C, with a maximum volume fraction of 0.2 vol.%. Using this experimental data, a nonlinear regression, ANN, and ANFIS models were utilized to anticipate the TC of nanofluids. On the basis of mean absolute percentage error (MAPE), ANN was shown to be the best model prediction strategy among these three models. Razavi et al.[135] developed a prediction model of thermal conductivities of nanofluids using

ANFIS and LSSVM. The prognostic models based on the LSSVM and ANFIS algorithms were compared using 15 types of correlation-based statistical indices. The results showed that the LSSVM method outperformed the ANFIS model. In a study by Said et al.,[19] the synthesis of a rGO/Co_3O_4 nanocomposite was accomplished, and the thermophysical characteristics were evaluated. The data were acquired under various experimental settings of concertation and temperature. In this study, the authors used a novel algorithm, namely, marine predators, for determining the optimal values of input controlling parameters (concentration ratio and temperature) that optimally minimizes two response variables (density and viscosity) at the same time while maximizing the other two response variables (specific heat and thermal conductivity). Said et al.[136] synthesized functionalized carbon nanofiber (F-CNF), carbon nanofiber (CNF), and rGO coated F-CNF (F-CNF/rGO). Furthermore, fuzzy logic techniques were used to develop an accurate prediction model based on the experimental data set. The observed values of thermal conductivity and the fuzzy model were found to be well-fitting. For thermal conductivity, the proposed numbers for fuzzy model rules were 16. The fuzzy model was trained for a total of 50 epochs. The thermal conductivity model had quite a low mean squared error (MSE) of 1.0709×10^{-5}, indicating superior prognostic efficiency.

In a study by Said et al.,[137] the heat transfer performance of a nanofluid combination was improved by utilizing a hybrid approach of fuzzy-based modeling with PSO. The TiO_2 and Al_2O_3 nanoparticles distributed in distilled ethylene glycol and water with 50:50 volumetric proportions are studied. Several volume fractions (0.05 and 0.3 vol%) and temperatures ranging from 25−70 °C were used to measure the nanofluid characteristics. The thermal conductivities at 25 °C improved by 9.52% and 26.52% for the Al_2O_3 nanofluid at 0.05% and 0.3% concentrations, respectively. At a 25 °C temperature of TiO_2 nanofluid with concentrations of 0.05% and 0.3%, the thermal conductivities could be improved by 7.77% and 18.05%, respectively.

Motlagh et al.[138] used GEP for model prediction of the TC of nanofluids including CuO and Al_2O_3 nanoparticles−water nanofluids. The derived novel model is dependent on nanoparticle size, volume fraction, and temperature. The model was built using the train data set, and the results were compared with the test data set. The findings showed that the GEP can accurately estimate and predict the TC of nanofluids and that it may be utilized to simulate engineering challenges. Pourrajab et al.[129] used GEP, linear genetic programming (LGP), and local weighted linear regression (LWLR) to develop a rigorous predictive model for ethylene glycol-based hybrid nanofluids. According to performance criteria, the LWLR model outperformed LGP (RMSE = 0.0259, R = 0.964) and GEP (RMSE = 0.0474, R = 0.865) in predicting thermal conductivities of hybrid nanofluids at RMSE = 0.014 and R = 0.988. Sensitivity analysis found that the temperature, volume fraction, and nanoparticle size were among the most important parameters. Table 2 lists some of the key research studies that used machine learning approaches to estimate the thermal conductivities of nanofluids.

4.2. Specific Heat. The specific heat capacity (SHC) of nanofluids is the degree of the heat retentive ability of the nanofluid. As a result, it determines the nanofluid's thermal behavior. Furthermore, the SHC capacity measurement can aid in estimating other thermally related characteristics such as

Table 2. Machine Learning Techniques in Model Prediction of Thermal Conductivities of Nanofluids

Reference	NF used	ML technique	Input	Performance parameter	Outcome
Maleki et al.[130]	NFs of ZnO particles	Multivariate adaptive regression splines (MARS), ANN, group method of handling data (GMDH)	TC of base fluids, volume percent of solid phase, particle size, and temperature	R^2 (ANN) = 0.9987, R^2 (GMDH) = 0.9980, R^2 (MARS) = 0.9879	Sensitivity analysis revealed thermal conductivity of base fluids being most important factor
Komeilibirjandi et al.[131]	NFs of ZnO particles	ANN, GMDH	TC of base fluid, temperature, mass fraction, and nanoparticle size	R^2 (ANN) = 0.9996, R^2 (GMDH) = 0.9826	ANN superior in model prediction of TC
Rostami et al.[132]	Paraffin/MWCNT	ANN, RSM	NF temperature and concentration	R (ANN) = 0.993, R (RSM) = 0.972	ANN better than RSM in model prediction of TC
Maleki et al.[133]	Silica nanoparticles in different base fluids	GMDH, ANN, scaled conjugate gradient (SCG)	TC of base fluid, temperature, mass fraction, and size	R^2 (ANN) = 0.9997, R^2 (GMDH) = 0.9991, R^2 (SCG) = 0.9998	All three techniques developed robust TC models
Alrashed et al.[134]	Carboxylic diamond and MWCNT dispersed in water	ANN, ANFIS	TC of base fluid, temperature, mass fraction, and size	MAPE (ANN) = 0.00842, MAPE (ANFIS) = 0.16294	ANN superior to ANFIS in model prediction of TC
Said et al.[19]	rGO/Co3O4 nanocomposite	Marine predator algorithm	Concentration ratio and temperature	–	For optimization of TC and SHC
Said et al.[136]	functionalized carbon nanofiber (F-CNF), carbon nanofiber (CNF), rGO coated F-CNF (F-CNF/rGO)	ANFIS	Concentration ratio and temperature	MSE = 0.0000107	ANFIS superior prognostic efficiency

thermal diffusivity, Nusselt number, and heat transfer rate.[63,139,140] In addition, the SHC is an important parameter for the proper assembly and design of heat transfer systems to minimize the loss of energy and increase the conservation of energy.[141,142] Several scholars have studied the specific heat capacity (SHC) of various nanofluids and their factors. The physicochemical characteristics of the nanofluid, such as the sizes of nanoparticles, volume fraction, temperature of the nanofluid, types of nanoparticles, and specific heat capacity of the base fluid affect the SHC of nanofluids.[63,143−145] Whereas numerical methods have provided an alternate solution to experimental investigation for evaluating the SHC of nanofluids, their precision has been limited by several factors, including presumptions controlling the relationship among variables, selectivity and an incomplete synopsis of the atypical nature of nanofluids.[41,56] Considering the aforementioned factors, computational technologies such as machine learning (ML) techniques are employed since they give a more accurate approximations.

Alade et al.[141] employed a support vector machine and ANN to prognosticate the specific heat capacity (SHC) of CuO/water nanofluids. The models were created using experimentally observed SCH data on CuO/water nanofluids at a volume % range from 0.4% to 2%, with temperatures ranging from 293 to 338 K. The findings showed that the SVR model was slightly superior to the ANN model. However, as compared to existing theoretical models, both the SVR and ANN models exhibit improved prediction abilities for the SHC of CuO/water nanofluids. Adun et al.[40] employed ANN for prognosticating the specific heat of a Fe_3O_4-alumina-zinc oxide/water ternary type hybrid nanofluid. The R^2 value indicating the coefficient of determination between observed and ANN model predicted values for specific heat was 0.9555. This indicates that the observed and projected specific heat values were in good agreement. Shi et al.[146] also used ANN for the development of a prognostic model for thermophysical properties of a carbon-magnetic type nanofluid. The objective of this research was to use experimental data on viscosity, thermal conductivity, and specific heat to build an ANN that could predict the thermophysical characteristics of magnetic nanofluids. The ANN model could predict the specific heat values within 5% of observed values, indicating an efficient predictive model.

To forecast the SHC of nanofluids, Jamei et al.[147] presented a Gaussian process regression (GPR)-based prognostic model. It was compared to the random forest (RF) technique and the generalized type regression neural network (GRNN). The GPR model (RMSE = 0.015 J/K.g, R = 0.9997) outperformed the RF (RMSE = 0.045 J/K.g, R = 0.9976) and GRNN (RMSE = 0.0608 J/K.g, R = 0.995) models in terms of performance. The results demonstrated that the proposed model could properly predict the SHCs of the nanofluids under study. Jamei et al.[63] used GEP for model prediction of specific heat using large data sets of diverse nanofluids. The SHC data of nanofluids, namely, Al_2O_3, ZnO, TiO_2, SiO_2, MgO, and CuO dispersed in various base fluids, were acquired from published studies. The GEP-based model was robust and efficient having an R value of 0.9570, RMSE value of 0.0650, and MAPE of only 5.5134. A summary of recent research works on machine learning-based model prediction of specific heat capacity is shown in Table 3.

4.3. Viscosity. Nanotechnology has attracted the interest of scientists, academics, and engineers during the last two decades because of rapid advancement. One of the unexpected

Table 3. Machine Learning Techniques in Model Prediction of Specific Heat Capacities of Nanofluids

Reference	NF used	ML technique	Input	Performance parameter	Outcome
Alade et al.[141]	CuO/water nanofluids	Support vector regression (SVR), ANN	Volume percent of solid phase, temperature	RMSE (ANN) = 0.0025 RMSE (SVR) = 0.0023	SVR slightly superior to ANN in model prediction
Adun et al.[40]	Fe_3O_4-alumina-zinc oxide/water ternary type hybrid nanofluid	ANN	Temperature, mass fraction, nanoparticle size	R^2 (ANN) = 0.9555	Observed and projected SHC values almost identical
Shi et al.[146]	Carbon-magnetic type nanofluid	ANN	Volume percent of solid phase, temperature	R = 0.95	Observed and projected SHC values almost identical
Jamei et al.[147]	Metal oxide and carbon-based nanoparticles in different base fluids	Gaussian process regression (GPR), random forest (RF), generalized regression neural network (GRNN)	Solid volume fraction, temperature, size of nanoparticles, SHC of base fluids	R (GPR) = 0.9997, R (RF) = 0.9976, R (GRNN) = 0.9956	All three techniques developed robust SHC models
Jamei et al.[63]	Several nanofluids	GEP	Solid volume fraction, temperature, size of nanoparticles, SHC of base fluids	R = 0.9570, RMSE = 0.065 MAPE = 5.5134	GEP proved an efficient model prediction technique
Hasan and Banerjee[148]	Molten nitrate salt mixture seeded with silica, alumina, and titania nanoparticles	ANN	Mass fractions, temperature	R^2 (ANN) = 0.9998, MAPE = 2%	Observed and projected SHC values in good agreement

consequences of this technology is nanofluids, which can dramatically improve the efficiency of thermal systems. Because solid nanoparticle-containing nanofluids have a greater viscosity than ordinary working fluids, evaluating the viscosity is important for building thermal systems and calculating pumping power.[149] Viscosity is one of the most significant thermophysical characteristics that influence how nanofluids transmit momentum and heat. The heat transfer performance of nanofluids requires an accurate estimate of this parameter.[84] Their dynamic viscosity heavily influences the thermal behavior and heat transmission capabilities of nanofluids. According to experimental investigations in this sector, the viscosity of nanofluids rises as the volume concentration of nanoparticles increases. According to studies, a nanofluid's viscosity decreases as the fluid's temperature rises.[150] This phenomenon results from the decline in intermolecular interaction between the nanoparticles and the base fluids due to temperature rise. The base fluids with high viscosities tend to minimize Brownian motion, resulting in less agglomeration as nanoparticles are less likely to collide. Nanofluids with high base fluid viscosities become steadily more stable than nanofluids with lower base fluid viscosities.[151,152]

Numerous forecasting models have been proposed for predicting dynamic viscosity based on influencing factors such as the sizes, types, and volume fractions of nanoparticles and also their temperature, using various methods such as ANN, ANFIS, SVM, PSO, GEP, GPR, and mathematical correlations.[153−155] In the recent decade, various models based using intelligent methods for the prediction of hybrid nanofluid viscosity have been proposed. The modeling technique employed, the data utilized for training the model, the choice of the input parameters, and so on all impact the efficacies and accuracies of these models. The models produced by various distinct machine learning methods are evaluated in this review article. Toghraei et al.[156] explored the viscosity of an ethylene-glycol/Ag nanofluid in temperatures ranging from 25 to 55 °C, having a volume percentage of nanoparticles ranging from 0.2% to 2%. A data set of 42 samples obtained from the experiment was used to create an ANN model to predict the dynamic viscosity. ANN model outcomes were compared with correlation findings. In comparison to the correlation approach, the ANN could accurately estimate the viscosity of the Ag/ethylene glycol nanofluid. The predictive model's MSE was 0.0012, with the highest amount of error as 0.0858. The dynamic viscosities of oxide nanoparticles suspended in water/ethylene glycol were model predicted using an ANN model by Longo et al.[157] This research used nanoparticle concentrations, temperatures, diameters of nanoparticles, average sizes of nanoparticle clusters, and base fluid characteristics for modeling. The ANN-based model predicted experimental data quite well, with a MAPE value of 4.15%. Chen et al.[158] also used ANN to model and forecast the viscosity of a hybrid type of nanolubricant (SAE50/MWCNTs-TiO$_2$). The performance of the ANN-based predictive model was compared with conventional curve fitting. The study concluded that ANN performs far superior to the conventional curve fitting model. Sedaghat and Yousefi[159] also used ANN to model and predict the viscosities of innovative graphene quantum dot nanofluids. With an R^2 = 0.99915 for the viscosity model, the overall predicted viscosities of nanofluids were in excellent agreement with experimental results. Baghban et al.[160] used ANFIS to prognosticate the viscosity of nanofluids. The voluminous experimental data (1277 data set) for model

development were collected from published research. The temperatures, densities of nanofluids, nanoparticle diameters, and viscosities of base fluids were used to correlate the viscosities of nanofluids. The model's robustness was demonstrated by a high R^2 of 0.99997. Furthermore, the absolute and maximum average relative deviations of 0.42% and 6.45% were reported. Hemmat Esfe et al.[161] presented a comprehensive study comparing three different artificial intelligence-based methods to forecast the viscosity of a nanolubricant (TiO$_2$/SAE 50). Genetic algorithm type radial basis function (GA-RBF) neural networks, LS-SVM, and GEP were used in the study. The models were evaluated on a statistical basis, and GA-RBF was found to be the most accurate among them. Researchers in the recent past have reported several other nonconventional and modern AI-based modeling methods. Bardool et al.[162] used friction theory for predicting nanofluid viscosity data. The repulsion and attraction pressure factors in the residual viscosity term of the friction model were included using the Esmaeilzadeh−Roshanfekr and Peng−Robinson equations of state. A total of 711 data sets obtained by experiments using a variety of nanofluids were used in modeling. The R-squared values for the Peng−Robinson and Esmaeilzadeh−Roshanfekr equations of state, respectively, were 0.9978 and 0.9979, showing extremely high performances of the proposed model. Yan et al[163] conducted a comparative study between ANFIS and SVM to model and predict the viscosities of MWCNTs-TiO$_2$/EG hybrid nanofluids over a range of temperatures and volume concentrations. Both approaches can accurately predict the rheological behaviors of MWCNTs-TiO$_2$/EG nanofluids based on their error calculations. The ANFIS technique, however, beats the SVM method in terms of accuracy. Shahsavar et al.[164] employed a GMDH type of NN to develop a prediction model for viscosity. The study reported a robust model to predict the viscosities of liquid paraffin and Fe$_3$O$_4$ nanofluid accurately. Ansari et al.[165] used various types of neural networks based on different training algorithms such as Bayesian regulation backpropagation (BR), scaled conjugate gradient (SCG), resilient backpropagation, and Levenberg−Marquardt (LM), including several transfer functions. Among these, the network architecture with one hidden layer and 23 neurons in the output and hidden layers with tan-sigmoid and purelin transfer functions was found to have the best performance. With an overall MSE value of 0.00901 and R^2 of 0.9954, the suggested network was robust enough to properly correlate and predict relative viscosity. Olumegbon et al.[166] employed a SVM-based model to forecast the viscosities of various carbon nanomaterials distributed in diesel oil. MWCNTs-graphene nanoplatelets and their hybrid were tested in the lab to acquire 120 experimental data points. The fluid temperatures, mass fraction of nanoparticles, and viscosity of diesel oil were chosen as model inputs. The training data set had an R of 0.9998 and an RMSE of 0.0076, whereas the testing data set had an R of 0.9999 and an RMSE of 0.0026. The suggested model was shown to predict the viscosities of carbon-based nanomaterials-diesel oil nanofluids with good accuracy. Table 4 depicts a summary of recent research studies on machine learning-based model prediction of viscosity.

4.4. Density. The literature review revealed that most of the emphasis had been dedicated to viscosity and thermal conductivity among the different thermophysical characteristics of nanofluids. The specific heat and density could not receive that much attention. In heat transfer applications as

Table 4. Machine Learning Techniques in Model Prediction of Viscosities of Nanofluids

Reference	NF used	ML technique	Input	Performance parameter	Outcome
Toghraei et al.[156]	Ag/wthylene-glycol nanofluid	ANN	Volume percent of solid phase, temperature	MSE (ANN) = 0.0858	ANN accurately estimates viscosity of Ag/ethylene glycol NF
Longo et al.[157]	Metal oxide nanoparticles suspended in water/ethylene glycol	ANN	Volume percent of solid phase, temperature	R² (ANN) = 0.9878	Observed and projected viscosity values in good agreement
Chen et al.[158]	Hybrid nanolubricant (SAE50/MWCNTs-TiO₂)	ANN	Concentrations, temperature	Compared with conventional curve fitting	ANN superior to conventional curve fitting
Baghban et al.[160]	Several nanofluids (1277 data sets)	ANFIS	Temperature, density of nanofluid, nanoparticle diameter, base fluid viscosity	R² (ANN) = 0.9999, Absolute average relative deviation (AAD) = 0.42%	ANFIS produced robust predictive model
Hemmat Esfe et al.[161]	TiO₂/SAE 50 nanolubricant	GA-RBF neural networks (GA-RBF), LS-SVM, GEP	Solid volume fraction, size, temperature of nanoparticles, SHC of base fluids	RMSE (GA-RBF) = 0.58 RMSE (LS-SVM) = 1.28 RMSE (GEP) = 6.59	GA-RBF performed superior to LS-SVM and GEP
Yan et al.[163]	MWCNTs-TiO₂/EG hybrid nanofluids	ANFIS, SVM	Mass fractions, temperature	R² (ANFIS) = 0.992, R² (SVM) = 0.987	ANFIS performed superior to SVM
Shahsavar et al.[164]	Liquid paraffin, Fe₃O₄ nanofluid	GMDH	Mass fractions, temperature	R² = 0.96, RMSE = 0.0179	GMDH type ANN efficient in model prediction of viscosity

applicable to renewable energy also, the heat transfer coefficient calculation requires the value of density.[167] Density also affects the nanofluid flow, so this parameter should be properly determined.[19,111] The addition of a modest number of solid nanoparticles to a base liquid would increase the density of the combination over time. This is because solids have a higher density than liquids. Estimating the material densities and volume concentrations of constituents is required for modeling densities in nanofluids.[168]

Several studies have been reported in recent years on lab-based measurement of nanofluid density. In an experimental investigation by Said et al.,[136] the densities of single and hybrid nanofluids were measured. The study found that the densities of nanofluids and base fluids decrease when the temperature rises, because of the liquid's thermal expansion. Compared to the base fluid, the average density rise for all nanofluids tested was less than 0.11%. Żyła et al.[169] measured the density of ethylene glycol (EG)-based nanofluids comprising three kinds of nitride nanoparticles: aluminum nitride (AlN), silicon nitride (Si_3N_4), and titanium nitride (TiN). Measurements were taken at three distinct temperatures: 308.15, 298.15, and 288.15 K. It was discovered that the proportion of nanoparticles has a considerable impact, but particle size does not affect density. The determination of a nanofluid's thermophysical characteristics is a tedious and onerous process in nanofluid research. Density measurement via experiment is expensive, and the parametric data range is limited. Numerical and analytical models need property values and interactions between base fluids and nanoparticles to be understood.[170] On the other hand, machine learning is capable of efficiently model predicting the densities of nanofluids over a large range of operating parameters.[171] Said et al.[137] used fuzzy to model predict the density using a range of operating conditions (vol % concentration and temperature). The study used the Al_2O_3 and TiO_2 nanoparticles distributed in 50:50 volumetric quantities of ethylene glycol and distilled water as nanofluids. Using the suggested technique, the optimum condition that generates the ideal output that minimizes the density while also maximizing thermal conductivity was obtained. Montazer et al.[172] used response surface methodology (RSM) to present a novel correlation for the estimation of carbon-based nanofluid density. The several machine learning methods applied for modeling thermophysical properties demonstrate that high prognostic efficiency can be achieved. Most machine learning techniques can accurately predict the outcomes. However, the efficacy of any machine learning technique depends upon the quality of data, the quantity of data, human efficiency in the measurement of thermophysical properties, human efficiency in data collection, the technique of data collection, and uncertainty in measurement. Nevertheless, the machine learning techniques are excellent means of model prediction, resulting in saving costs and human efforts. A summary of recent research studies employing machine learning for model prediction of density is illustrated in Table 5.

5. MACHINE LEARNING FOR RE

The renewable energy system does suffer from a certain degree of uncertainty in demand and supply balancing. Demand response (DR) has gained popularity in recent years as a cost-effective approach to provide flexibility, thus enhancing the energy network dependability. However, because of the high complexity of DR activities, the frequent requirement for near

Table 5. Machine Learning Techniques in Model Prediction of Densities of Nanofluids

Reference	NF used	ML technique	Input	Performance parameter	Outcome
Said et al.[137]	Al_2O_3 and TiO_2 nanoparticles dispersed in deionized water and EG	ANFIS	Volume percent of solid phase, temperature	R^2 (ANN) = 0.9982	ANFIS accurately estimates densities of nanofluids
Kumar et al.[42]	MWCNT-water-based Al_2O_3, TiO_2, ZnO, CeO_2 nanofluids	ANN	Volume percent of solid phase, temperature	R = 0.999, MSE < 0.001	Observed and projected density values in good agreement
Mirsaeidi and Yousefi[173]	Water–ethylene glycol mixture and carbon quantum dots (CQDs) nanofluids	ANN	Concentrations, temperature	R^2 = 0.9999, AAD = 0.01%	ANN produced robust predictive model for density
Yousefi and Amoozandeh[174]	Sb_2O_5, ZnO/(EG+H_2O), SnO_2/(EG+H_2O), ZnO/(PEG+H_2O), Al_2O_3/(EG+H_2O), TiO_2/EG, ZnO/PEG	ANN + Principal component analysis (PCA)	Temperature, volume fractions	AAD (ANN) = 0.01%	ANN developed robust predictive model for density
Singh and Ghosh[175]	Alumina/distilled water (DW), MWCNT)/DW, graphene nanoparticle/DW	ANN	Temperature, volume fractions	Maximum error in density measurement < 0.2%	ANN produced robust predictive model for density
Giwa et al.[176]	Alumina/distilled water (DW), MWCNT)/DW	ANFIS, ANN	Base fluid, mass fractions. temperature	RMSE (ANFIS) = 0.154, RMSE (ANN) = 0.133	ANN performed superior to ANFIS

real-time choices, and the utilization of large-scale data, machine learning methods have lately been developed as essential technologies. AI may be employed to solve a variety of problems such as predicting demand, raw material supply, seasonal cost variations, dynamic pricing, scheduling, and control.[59]

5.1. Heat Exchangers. The heat exchanger is essential equipment in the renewable and sustainable energy sectors. The hydrodynamic and heat transport properties of heat exchangers significantly impact the performance of renewable and sustainable energy systems.[177,178] There are various methods for increasing a heat exchanger's efficiency. The use of working fluids with improved thermal characteristics would be the most efficient of these strategies.[179] Nanofluids are a viable alternative for improving heat transmission in heat exchangers due to their outstanding thermophysical characteristics.[180] Because of the relevance of nanofluids, numerous researchers explored their performance and use in various heat exchangers.

The double pipe heat exchanger (DPHE) has been used extensively in industrial applications such as power plants, air conditioning, refrigeration systems, water heaters, and petrochemicals. Thermal conductivity is a significant factor in enhancing the heat transfer rate of fluids.[181−183] Many attempts have been made to introduce fine solid particles in the base fluid to enhance the TC.[184−187] Ali et al.[188] explored the heat transfer properties of a MgO oil-based nanofluid used in a double-pipe heat exchanger. The study discovered a considerable improvement in the heat transfer rate and total heat transfer coefficient. Alumina nanoparticles were utilized with a base fluid in the majority of the works.[189−191] Chun et al.[189] reported that the use of alumina nanoparticles in the DPHE significantly increases the coefficient of heat transfer. In an experimental study, Abd Elhafez et al.[186] found the enhanced thermal performance of a DPHE with an Al_2O_3 nanofluid in specific ranges with no significant pressure drop penalty. Mansoury et al.[191] studied the performance of the DPHE, plate type heat exchanger, and STHEx, in which Al_2O_3/water nanofluid (0.2%, 0.5%, and 1% vol %) concentrations were employed. The study revealed that a DPHE exhibited the best performance with an improvement of heat transfer coefficient by 60%. Saeedan et al.[192] used the water-based nanofluids of Cu, CuO, and CNT nanoparticles in the DPHE. Effects of Reynolds number and volume concentration were also investigated. It was observed in the study that rises in the Reynolds number and volume concentration enhance the heat transfer coefficient. Sarafraz and Hormozi[193] explored the effect of rate of flow rate and vol % concentration on the coefficient of heat transfer. Water/ ethylene-glycol (50:50 by volume) was used as a base, whereas particles were extracted from green tea leaves and silver nitrate. An enhancement of 67% was reported in the heat transfer coefficient at vol % = 1. Bahiraei et al.[194] explored the efficacy of silver particle-based NF in the DPHE. The study revealed that particle migration increased the heat transfer rate, whereas rises in the concentration and Reynolds number resulted in improved heat transfer. Ravi Kumar et al.[195] used a Fe_3O_4 nanofluid in the DPHE. The nanoparticles utilized in this work have volume concentrations of 0.005%, 0.01%, 0.03%, and 0.06%, with Reynolds numbers in the range from 15,000 to 30,000. Nusselt number enhancement by 14.7%, compared to the base fluid, was reported in the study for the concentration of 0.06% and Reynolds number of 30,000. Shakiba and

Vahedi[196] studied the influence of a magnetic field over hydrothermal characteristics of a ferrofluid in a DPHE and found that there were increases in Nu number, pressure drop, and friction factor. This was attributed to the transverse magnetic field changing the axial velocity profile. Sözen et al.[197] experimentally showed that using alumina and fly ash nanofluids in heat exchangers improved the efficiency. As a result of the existing literature's research, it has been established that using nanofluids in heat exchangers greatly improves their thermal performance.

To improve the performance of the plate-type heat exchanger (PHE), two major variables must be considered: the amount of pressure drop and heat transfer. The degree of heat transfer must be raised while the pressure drop must be lowered. Several optimization studies have been carried out for PHEs.[198−202] Pandya et al.[203] reviewed the enhancement of heat transfer enhancement using nanofluids in PHEs. Several authors reviewed and identified the various heat transfer enhancement techniques in PHEs, such as louver fin, corrugated fin, perforated fin, artificial roughness, extended surface, winglets, and staggered wavy fin.[204−206] Inserts and vortex generators were also studied as heat transport improvement strategies.[207] A modification to the plate was also made to improve heat transfer.[208,209] The chevron angle was found as the significant geometrical parameter in heat transfer improvement.[210] Besides the above approaches, nanofluids are also attractive solutions to improve the efficiencies of heat exchangers. Because of the growing importance of nanofluids, many researchers explored the performances of PHEs employing nanofluids.[211,212] In general, researchers studied the pressure drop and heat transfer characteristics.[213,214] Many scholars numerically investigated the applications of nanofluids in the PHEs.[215−217] Various nanoparticles like SiO,[218,219] TiO2,[220] CNT,[221,222] Al2O3,[223−225] Ag,[226−228] CuO,[229] ZnO,[230] and hybrid nanoparticles[231−234] have been studied to improve the performance of the PHEs. Kumar et al.[235] investigated the effect of nanofluid flow on the performance of the square channel. Attalla and Maghrabie[224] employed an Al2O3/water nanofluid to evaluate the performance of the PHE. Experiments were conducted for various surface roughness values and different volume concentrations with Re ranging from 500 to 5000. Estimates were made for the friction factor, Nu number, and heat transfer enhancement factor. It was concluded that enhancing the vol % of nanoparticles improves the heat transfer rates and pressure drops in PHEs. Despite having a larger pressure drop and friction factor than the base fluid, MWCNT/water nanofluids showed improved overall thermal performances.[221] Similarly, Goodarzi et al.[222] also reported that the performances of PHEs could be improved by using MWCNT. Fouling of the nanoparticles over the inner body of the heat exchanger generally enhances the roughness, thermal resistance, friction factor, and drop in pressure. Sarafraz et al.[229] used a low-frequency vibration, which improved the heat exchanger's thermal performance. The latest research work in STHEx revealed that nanofluids containing different types of nanoparticles such as Ag,[236] CuO,[237] Al2O3,[238] TiO2,[239] and graphene oxide[240] outperformed their respective base fluids in terms of thermal performance. Nazarzade et al.[236] experimentally explored the forced convective heat transfer in STHEx with a silver/water nanofluid. Silver nanoparticles were first synthesized using a reduction process and then dispersed in water to make the nanofluid. The results showed that

nanofluid had a higher overall heat transfer coefficient compared to water as a base fluid at similar mass flow rates. In a similar finding, Said et al.[237] reported an increase of 7% in the overall heat transfer coefficient and an increase of 11.39% in convective heat transfer and achieved a reduction of 6.81% in the area. Somasekhar et al.[238] conducted a numerical study to know the heat transfer characteristics and pressure drop of an Al2O3/water nanofluid and distilled water in a shell and tube heat exchanger. An Al2O3/water nanofluid was revealed to be a better cooling medium than distilled water in the study; however, the use of an Al2O3/water nanofluid as a cooling medium increased the pressure drop on the tube side in comparison to the distilled water. Ullah et al.[239] numerically investigated the heat transfer properties of TiO2/water and γ-Al2O3/water nanofluids in the STHEx. The influences of the Reynolds's number of suspended nanoparticle vol % and particle type were examined on the thermal properties. The results discovered the peak improvement of 41.8% in the convective heat transfer coefficient for Al2O3/water, whereas TiO2/water exhibits a maximum increase of 37%. According to the study, the introduction of nanofluids increases the pressure drop, and the explanation for this was attributed to the nanofluid's higher viscosity than the base fluid. Esfahani and Languri[240] used graphene oxide as a nanofluid in the shell and tube heat exchanger and performed an exergy analysis. Exergy analysis revealed that raising the graphene oxide concentration from 0.01 to 0.1 wt % increased heat conductivity by 8.7% and 18.9% at 25 and 40 °C, respectively. Investigation showed a reduced level of exergy loss in the STHEx in both laminar and turbulent conditions by employing graphene oxide nanofluids. Lotfi et al.[241] experimentally studied the enhancement in heat transfer by using the MWCNT/water nanofluid in a horizontal STHEx. In comparison to the base fluid, the results show that heat transfer was improved because of the presence of MWCNT.

According to the findings of the preceding research, various nanoparticles had varying influences on the performances of the heat exchangers. Furthermore, the thermal performance of heat exchangers is affected by a variety of elements such as nanofluid characteristics, and structural−geometrical features.[242] In this case, machine learning might assist in resolving the difficulties of heat transfer and nanofluid flow, as well as providing realistic thermal design assistance to increase the efficiency of various types of heat exchangers. Various machine learning techniques have been employed to analyze the thermal and hydrodynamic performances of heat exchangers with nanofluids. Saeedan et al.[192] proposed a neural network model to forecast the pressure drop and Nusselt number. The value of the Nusselt number was assessed concerning the maximum relative error and MSE values of 1.2596% and 0.409%, respectively. However, the pressure gradient value was predicted concerning maximum relative error and MSE values of 0.25% and 0.08%, respectively. Xie et al.[243] applied the ANN for analyzing the heat transfer in the STHEx. For training and testing neural network configurations, lab-based experimental data were gathered. Overall heat transfer rates and temperature variations at the outlets on either side were anticipated. Different network designs were investigated to determine the best network for prediction, and ANN was shown to be superior. The maximum variation between experimental and predicted data was determined to be less than 2%. In a similar study, Wang et al.[244] reported that the ANN approach is better than empirical correlations for predicting heat transfer rates

Table 6. Summary of Recent Research on Heat Exchangers Utilizing Nanofluids and Models Anticipated Using Machine Learning Approaches

References	Type of heat exchanger studied	NF used	ML technique used	Input	Output	Performance parameters	Outcome
Xie et al.[243]	Shell-and-tube heat exchanger	—	ANN	Reynolds number, inlet temperature, total no. of tubes, diameter of center tube, total no. of baffles, baffle pitch	Temperature difference, heat transfer rate	R = 0.9954	Prediction from ANN found to be much more precise than correlation
Hojjat[246]	Shell-and-tube heat exchanger	TiO$_2$/water Al$_2$O$_3$/water	ANN	Nanoparticle volume concentration, Reynolds number, nanoparticle thermal conductivity, Prandtl number	Nusselt number, pressure difference	For Nusselt number, R = 0.9944, mean squared error (MSE) = 0.0009, For pressure drop, R = 0.9991, MSE 0.0002	9% average difference found between experimental data and predicted values of Nusselt numbers by ANN
Maddah et al.[247]	Double-pipe heat exchanger	SiO$_2$/water	ANN	Re, Pr, particle concentration, Tr, GPR	Exergetic efficiency	R^2 = 0.9779	ANN determined optimal plan of operation for heat transfer process
Bahiraei et al.[248]	Concentric tube heat exchanger	Cu nanoparticles and base fluids, carboxymethyl cellulose (CMC), water (0.4 wt %)	ANN-genetic algorithm (GA)	Radius ratio, volume concentration, particle size	Convective heat transfer coefficient, pressure drop	For heat transfer coefficient of inner wall, R^2 = 0.999 MRE = 0.0110	ANN model estimated data accurately
Safikhani et al.[249]	Flat tubes	Al$_2$O$_3$/water	For modeling GMDH type ANN. NSGA II for optimization	Particle concentration and size, heat flux, volumetric flow rate	Convective heat transfer coefficient, pressure drop	For heat transfer coefficient R^2 = 0.9802 MAPE = 0.2108	Comparison of results between ANN and CFD gave error less than 5%
Zdaniuk et al.[250]	Straight tubes with internal helical fins	—	ANN	Number of fins starts, helix angle, Re	Colburn j-factors, Fanning friction factors	For j, MSE = 7.7760 x10^{-9} For f, MSE = 7.7760 x10^{-9}	ANN found superior to corresponding algebraic power law regressions
Wijayasekara et al.[251]	Compact heat exchanger	—	EBaLM-OTR	Mass flow rate, hot and cold side inlet temperature, pressure	Pressure drop, heat transfer	Error less than (10^{-5} to 10^{-3})	EBaLM-OTR used for overtraining resilience

and recommended that ANN be used to model heat exchangers and simulate thermal systems. Xie et al.[245] The Nusselt numbers and friction factors of three types of fin-and-tube heat exchangers were correlated using the ANN. Twelve geometric parameters were fed into ANN, and the outputs were the Nusselt number and friction factor. NN was trained, and the weights were adjusted using the well-known feed-forward backpropagation method. The disparity between forecasts and experimental data was discovered to be less than 4%. Hojjat[246] developed the ANN to forecast the thermal and hydrodynamic performance of nanofluids used in STHEx. Volume concentration, Reynolds number, nanoparticle thermal conductivity, and Prandtl number were used as the inputs in the ANN model. Deviations in experimental data and ANN results were almost 9% and 9.6% for Nusselt Number and pressure drop, respectively. In another study, Maddah et al.[247] performed the exergetic efficiency and used the different concentrations of nanofluids with twisted tape in double-pipe heat exchangers. Exergetic efficiency predictions from experimental processes were difficult and time consuming. ANN was utilized to identify the correlation between the thermal and flow parameters and the exergetic efficiency. Bahiraei et al.[248] investigated the convective heat transfer in STHEx. It was reported that the impact of altering concentration on pressure drop was greater than the impact of radius ratio and particle size. ANN was used to create a forecast model for convective heat transfer. GA in a combination compromise programming technique was used to determine the optimum conditions with the most heat transfer and the least pressure loss. Safikhani et al.[249] employed the multiobjective optimization for Al_2O_3/water nanofluid in the flat type tubes by using ANN, computational fluid dynamics (CFD), and nondominated sorting genetic algorithms (NSGA II). To obtain the correlation between the Fanning friction factors and Colburn j-factors for the flow of water in straight-type tubes, Zdaniuk et al.[250] used the ANN. It was concluded that ANN was superior to its corresponding algebraic power law regressions. Wijayasekara et al.[251] highlighted the risk of overtraining or overlearning the network. Generalizing is the main goal of the network. The authors used the EBaLM-OTR (error backpropagation and Levenberg−Marquardt algorithms for overtraining resilience) method to overcome this problem. In this method, neural network architecture evaluates alternative network topologies based on mean square error (MSE) and standard deviation of MSE using a separate validation set. The approach has proven to be a valuable tool for identifying the flaws and benefits of various network topologies. The above literature survey showed that ANN is the most common machine learning technique used to predict different parameters in the heat exchangers. The survey also reveals that the training database may be enlarged to incorporate experimental and numerical data for improved prediction. Table 6 summarizes current work on heat exchangers utilizing nanofluids and models predicted using machine learning approaches.

5.2. Solar Energy Systems. A solar-based photovoltaic (PV) energy system is the most common form of renewable energy source, having a huge presence in energy markets.[252,253] This is because the Sun's continuous solar energy of 1367 W/m² is distributed throughout the atmosphere. The total amount of energy absorbed by the planet from solar radiation at any instance is estimated as 1.8×10^{11} MW.[54] Solar's enormous potential for generating sustainable energy has piqued the interest of policymakers, economists, governments, and environmental engineers.[254,255] PV energy thus offers enormous promise for urban as well as rural electrification.[256,257]

On the other hand, PV power generation is impacted by a variety of factors like humidity, weather, solar radiation, wind pressure, and ambient and module temperatures.[258] Natural climatic fluctuations may change these factors, affecting the quantity of electricity generated. The power system's dependability, stability, and planning are all disrupted by a sudden shift in solar power production.[259] To avoid such situations, accurate and exact solar power output forecasting is needed to maintain the power system's reliability, stability, and quality.[260] It has the potential to decrease the grid's effect from power unpredictability. One of the most essential problems for the near future global energy supply will be the considerable integration of renewable energy sources (particularly solar) into existing or future energy supply architecture.[261] An electrical operator must maintain a perfect balance between power output and consumption at all times. In practice, the operator frequently faces challenges in maintaining this balance with traditional and controlled energy production systems, particularly in small or isolated electrical grids (as found in islands).[262]

Machine learning techniques such as SVM, ANN, extreme learning machine (ELM), GA, and GEP can model predict the generation and uncertainties in the solar energy domain. These models are useful for pattern recognition, classification, data mining, and forecasting because they can build a connection between inputs and outputs even when representation is difficult.[263,264] Meenal and Selvakumar[265] employed SVM, ANN, and empirical methods for the prediction of solar radiation. Modeling inputs were month, longitude, latitude, day length, brilliant sunlight hours, relative humidity, and temperature range. It was observed that month, peak temperature, latitude, and bright sunlight hours were the most affecting input parameters, whereas relative humidity is the least influential. SVM was superior to ANN and empirical models in prognostic modeling. Fan et al.[266] also used SVM to study the influence of air pollution on solar radiation. Six common constituents of air pollution (NO_x, SO_2, O_3, CO, $PM_{2.5}$, and PM_{10}) and air quality index (AQI) were used as input for modeling the diffuse and global solar radiations. The SVM model predicted that the AQI was the most influencing factor affecting both diffuse and global solar radiations. Eseye et al.[267] used a hybrid approach of the PSO-SVM-wavelet method to forecast the photovoltaic (PV) solar power. The interactions of the PV system's real power record with numerical weather prediction (NWP) meteorological data over one year using a 1 h time increment were used for modeling. The hybrid approach demonstrated superior performance to standalone model prediction techniques. Fan et al.[268] also used a hybrid approach to study air pollution's influence on daily diffuse solar radiation. SVM with PSO, BAT, and the whale optimization algorithm (WOA) were recommended for diffuse daily solar radiation prediction in air-polluted locations. SVM models outperformed extreme gradient boosting (XGBoost) and MARS models, while the BAT method was the most effective in improving the performance of solo SVM models. Lee et al.[269] developed a prediction model for solar irradiance using ensemble machine learning techniques. A summary of recent studies on applications of nanofluids in solar thermal systems and

model prediction with machine learning techniques is depicted in Table 7.

5.3. Geothermal Energy. The shift from fossil-fuel-based systems to renewable-energy systems is becoming critical for sustainable energy development and environmental protection. Geothermal energy is a promising renewable type of energy and has the potential to reduce fossil fuel usage and minimize environmental impacts.[275−277] Because of the growing importance of geothermal energy systems, many researchers reviewed the various aspects.[278,279] In general, geothermal power plants have low operating costs[280,281] but on the other hand have lower energy conversion efficiencies than typical thermal power plants.[282,283] The reason is attributed to the relatively low temperature of geothermal resources.[284] This is the major technological challenge that restricts the widespread application of geothermal energy.[285] The efficiency of heat conversion could be raised by improving the heat transfer between the ground and heat-carrying fluid. Due to better thermophysical properties than the base fluids, nanofluids could be a good alternative for a heat carrier fluid.[286]

Daneshipour and Rafee[287] applied Al_2O_3/water and CuO/water nanofluids as the working fluids of a geothermal borehole heat exchanger. The Reynolds averaged Navier−Stokes (RANS) equations were numerically solved with the SST k-turbulence model to simulate the flow. The results reveal that the heat exchanger's overall water flow pressure loss is minimized at a particular diameter ratio. The findings also reveal that the CuO−water nanofluid extracts more heat than the alumina−water nanofluid, albeit at the expense of larger pressure losses and pumping powers. Diglio et al.[288] numerically investigated the use of different nanofluids in the borehole heat exchanger. The optimal nanofluid is determined using a computational model based on energy and momentum balances. It is found in the study that copper has the biggest borehole thermal resistance decrease, reaching around 3.8% when a nanoparticle's volumetric concentration is 1%, but it also has the second-highest pressure drop. A summary of recent studies on applications of nanofluids in solar thermal systems and model prediction with machine learning techniques is depicted in Table 8.

5.4. Wind Energy. Wind power is a significant renewable energy source, and its growth is helpful in terms of energy supply security and lowering greenhouse gas emissions.[293,294] The wind power curve plays an important role in estimating wind energy potential and wind turbine selection.[295−297] Wind turbines must disperse a substantial quantity of heat during operation. The produced heat must be effectively distributed; otherwise, the temperature of the mechanical and electrical components would rise, lowering overall energy efficiency. The cooling system is used to dissipate the heat. Raj et al.[298] employed nanofluid in the cooling system of the wind turbine. The use of nanofluid reduces the heat transfer surface and the flow rate of heat transfer fluid due to the greater thermal conductivity. De Risi et al.[299] employed Al_2O_3/water nanofluid to increase the performance of the cooling system. This cooling system limits the thermal stresses in the electrical and mechanical components of the wind turbine. In their study, Álvarez-Regueiro et al.[300] determine that the wind turbines having a capacity above 10 MW require a sophisticated cooling system. Empirical relation functions for the Nu number and Darcy friction factor were developed. The use of nano-enhanced industrial coolant enhanced the convective coefficient of heat transfer by 7% for the nanofluid with

Table 7. Summary of Recent Research Conducted on Solar Thermal Systems Using Nanofluids and Models Predicted with Machine Learning Techniques

Reference	Type of solar energy application and NF	ML technique used	Input	Output	Performance parameters	Outcome
Jamei et al.[143]	Generic solar thermal with molten (nitrate) salt-based nanofluids	AdaBoost, Extra Tree Regression	Solid mass fraction, SHC of base fluids, temperature, density, mean diameter	SHC of NF	R= 0.9964, RMSE = 0.1566	SHC of BFs was most vital parameter in estimation of NF SHC
Jamei et al.[147]	Generic solar thermal with carbon and metal oxide based nanofluids	Gaussian process regression	Temperature and SHC of base fluids, mean diameter and solid volume fraction of nanoparticles	SHC of NF	R = 0.9997, RMSE = 0.01506	Mean diameter of nanoparticles and SHC of BFs was most vital parameter in SHC of NFs estimation
Cao et al.[270]	Efficiency of thermal/PV collectors with nanocoolants	ANN, least square support vector regression, ANFIS	NFs properties, flow rate of coolant, solar radiation	Electric efficiency	R^2 = 0.9534, MSE = 2.548	Performance could be simulated efficiently
Ranjan Parida et al.[271]	Generic solar thermal with molten (nitrate) salt-based NFs	Principal component analysis (PCA), hierarchical cluster analysis (HCA)	Concentration, density ratio, temperature, nanoparticles size	SHC of NF	81.3% variations in entire data set	Mean diameter of nanoparticles was most vital parameter in SHC of NFs estimation
Ebrahimi-Moghadam et al.[272]	Parabolic trough solar collector with Al_2O_3 and ethylene glycol	ANN	Reynolds number, mean flow temperature, particle size	Optimal volume fraction	R^2 = 0.9992, MSE = 5.92×10^{-9}	Optimal volume fraction not influenced by Re number
Delfani et al.[273]	Direct absorption solar collector with graphene oxide/deionized water	ANN	Solar collector length and depth, fluid flow rate, concentration, temperature difference	Nusselt number, collector efficiency	For efficiency MAPE = 1.47%, for Nusselt number MAPE = 2.567%	Highly precise predictor model developed using ANN
Bahiraei et al.[274]	Solar still with Cu_2O nanoparticles	ANN, PSO-ANN, ANFIS	Fan power, nanoparticle volume fraction, glass, basin, water temperature	Energy efficiency	R^2 = 0.9884 for PSO-ANFIS	PSO-ANFIS hybrid approach superior in model prediction

Table 8. Recent Studies Conducted on Geothermal Energy Systems Using Nanofluids and Models Predicted with Machine Learning Techniques

Reference	Nanofluids	ML technique used	Input	Output	Performance parameters	Outcome
Narei et al.[289]	Al$_2$O$_3$ + water	Multiobjective flower pollination algorithm	Effective thermal conductivity, viscosity	Convective heat transfer	–	Helped in bore length reduction by 1.3%
Ramezanizadeh and Nazari[290]	Metallic nanoparticles in water	GMDH-ANN	Temperature, solid vol %, SHC of base fluids, mean diameter of nanoparticles	SHC of NF	R^2 = 0.99	GMDH-ANN could develop a robust predictive model
Alade et al.[141]	CuO + water	ANN, SVR	Solid volume fraction, temperature	SHC of NF	RMSE (ANN) = 0.0025, RMSE (SVR) = 0.0023	SVR performed better compared to ANN
Hemmat Esfe et al.[291]	Al$_2$O$_3$ + water	ANN + NSGA II	Concentration, temperature	TC and dynamic viscosity of NF	MSE = 0.0008	ANN with NSGA II creates a robust meta model
Tiwari et al.[292]	CNT + water	ANFIS	Angular rotational velocity, Richardson number, nanoparticle volume fraction	Nusselt number	RMSE = 0.924, R^2 = 0.9921	Average Nusselt number enhancements up to 64%

nanoadditive loading of 0.25 wt %. Rostamzadeh and Rostami[25] employed the waste heat captured from the cooling system of the wind turbine for the desalination process. Cu, CuO, TiO$_2$, Al$_2$O$_3$, and SiO$_2$ nanoparticles were employed with a water base fluid. A Cu/water mixture had the best performance of all the nanoparticles used because it produces more freshwater, whereas the SiO$_2$/water mixture has the lowest efficiency. A summary of recent work in the domain of model prediction/numeric simulations for wind energy systems using nanofluids is listed in Table 9.

5.5. Other Renewable Energy Systems. Modern machine learning methods powered by high-speed computational machines are making huge differences in several renewable energy fields. Biomass is currently the world's most extensively utilized renewable energy source. It is mostly utilized as a solid fuel, with liquid fuels and gas being used to a lesser amount.[302,303] The utilization of biomass for energy generation has risen slowly in recent years. Rural and off-grid regions rely heavily on biomass for energy.[304] Biomass is utilized to satisfy a wide range of energy requirements, including producing electricity, powering cars, heating homes, and supplying process heat for industrial operations. Wood, animal, and plant wastes all have biomass potential.[305,306] Biomass can be directly used as fuel, although direct combustion is highly inefficient and polluting. The biomass can be converted to fuel in liquid or gaseous.[307,308] Among the biomass conversion methods, pyrolysis has a lot of promise.[309,310] Thermochemical conversion, which includes combustion, pyrolysis, torrefaction, hydrothermal liquefaction, and also gasification, is the most practical method for converting solid biomass into biofuel.[311,312] By optimizing process parameters, the fundamental objective of thermochemical conversion is to remove unwanted byproducts. Pyrolysis is a potential technology for converting biomass into biofuel in an inert environment at high temperatures (250−600 °C).[313,314] Pyrolysis technology is being used to produce biobased fuels and chemicals from biomass, which is a relatively new technique. Bio-oil, biochar, and syngas are the end products of biomass pyrolysis, and they might be used for energy generation or other applications with exceptional characteristics such as environmental friendliness, cheap prices, and biodegradability.[310,315]

The process of biomass conversion is highly nonlinear. Several researchers applied machine learning methods such as ANN[316] and GEP[317] to model predict the biomass conversion to usable fuel, biofuels, and its byproducts. Safarian et al.[318] employed the ANN technique for model prediction of a downdraft biomass gasification-integrated power generating unit. The aim was to estimate the net output power of systems using biomass feedstocks under diverse operating conditions and atmospheric pressure. Compositions of feedstock, proximate type analysis (ash, moisture, fixed carbon, and volatile material), and operational parameters were utilized as input parameters. The ANN model exhibited robust prediction with observed data with R^2 greater than 0.999. Mutlu and Yucel[319] used machine learning classifiers for the prediction of gasification products. Two types of classifiers were used: binary least squares support vector machine and multiclass random forests classifiers. The suggested methods were developed and validated using 10-fold cross-validation on 5237 data samples, with binary and multiclass classifiers achieving prediction accuracy values of over 96% and 89%, respectively.

Table 9. Recent Studies Conducted on Wind Energy Systems Using Nanofluids and Models Predicted with/without Machine Learning Techniques

Reference	Nanofluids	ML technique used	Input	Output	Performance parameters	Outcome
Álvarez-Regueiro et al.[300]	Havoline XLC Premixed 50/50	Dimensionless analysis-based estimation	Nanoadditive loading, temperature, Reynolds number	Convective heat transfer coefficient, pressure drop	Nu number, Darcy function	Peak coefficient of heat transfer increased by 7% for 0.25% nanofluid concentration
Maleki et al.[130]	ZnO + water	ANN, multivariate adaptive regression spline (MARS)	Base fluid TC, concentration, temperature, nanoparticle size	TC of NF	R^2 (ANN) = 0.9987, R_2^2 (MARS) = 0.9879	ANN performed better compared to MARS
Komeilibirjandi et al.[131]	CuO with water	GMDH-ANN	Base fluid TC, concentration, temperature, nanoparticle size	TC of NF	R^2 = 0.9996, AARD = 0.881%	GMDH-ANN could develop a robust predictive model
Adun et al.[301]	Al_2O_3-ZnO–Fe_3O_4	Gaussian process regression	Concentration, mixture ratio, temperature,	TC, dynamic viscosity of NF	R^2 (TC model = 0.9987, R^2 (viscosity model) = 0.034	ANN with NSGA II creates robust metamodel

Baruah et al.[320] developed an ANN-based biomass gasification model using ANN to forecast the product gas composition in terms of concentrations of four key gas species: CH_4, CO_2, CO, and H_2 percentwise. Biomass composition and reduction zone temperature were utilized as input parameters in the models. The output of the ANN models was found to agree with experimental data with absolute fractions of variance (R^2) more than 0.99 for CH_4 and CO models and greater than 0.98 for CO_2 and H_2 models. An ANN model was created by Kargbo et al.[321] utilizing experimental data to forecast the gasification process. The study's objective was to use AI-based model prediction, resulting in saving time and money in the development and testing process. With a correlation of $R^2 > 0.99$, the ANN-based model could reliably forecast gas composition and yield in response to output changes. Aghbashlo et al.[322] used a hybrid ANFIS-PSO approach to predict lignocellulose pyrolysis kinetic constants. The PSO technique was employed to fine-tune the membership function parameters of the ANFIS model. With an $R^2 > 0.970$ and a MAPE = 3.27%, the generated models were able to accurately predict the pyrolysis behaviors of three distinct biomass feedstocks with $R^2 > 0.91$, indicating their fidelity. Elmaz et al.[323] employed four regression techniques: support vector machine, polynomial regression, decision tree regression, and ANN to forecast CO, H_2, CO_2, CH4, and high heating values from the biomass gasification process. To avoid multicollinearity and enhance the computing efficiency, the extracted features are subjected to principal component analysis. The ANN and decision tree regression outperformed others by attaining $R^2 > 0.9$ for the majority of outputs.

In the field of renewable energy and, more specifically, the solar energy domain, battery energy storage systems are the basic necessity. The uncertainties in optimal scheduling and operation of a renewable energy system need efficient machine learning techniques for modeling.[324] Masoumi et al.[325] successfully used an ANN-PSO hybrid approach to model and predict the uncertainty in optimal renewable energy allocations combined with battery energy storage. The researchers integrated the modeling of solar-, wave-, and wind-based renewable energy systems. A battery storage system was employed to compensate for any uncertainty caused by the renewable energy system. It was concluded that the use of electric vehicles and their aggregators could assist system operators in maximizing their benefits in terms of power quality and market control. In another study by Gayen and Jana,[326] the ANFIS-based control strategy improves the overall control capabilities for microgrid-connected battery energy storage systems. Several simulation studies were done on a 230 V, 50 Hz single-phase ac grid linked 100 Ah, 120 V battery using MATLAB-SIMULINK 2014b software to test the enhanced control approach. Using ANFIS, the efficiency of a coordinated regulating strategy for transferring power between a battery and single-phase type electrical grid was enhanced. A summary of recent work in model prediction for the various renewable energy systems is listed in Table 10.

6. CHALLENGES AND PERSPECTIVES

The application of machine learning has grown in importance as a technique for studying system behavior and evaluating system performance. It is increasingly being applied in nanofluids and renewable energy systems, although its potential and prospects are yet to be completely realized.

Table 10. Recent Research Conducted on Various Renewable Energy Systems Model Predicted with Machine Learning Techniques

Reference	ML technique used	Input	Output	Performance parameters	Outcome
Sharma[316]	ANN, GEP	Engine load, fuel blending ratio, injection parameters	Brake thermal efficiency, brake specific energy consumption,	R (GEP) = 0.997 R (ANN) = 0.9998	ANN marginally superior to GEP in model prediction
Sharma[317]	GEP	Engine load, fuel blending ratio, injection parameters	Brake thermal efficiency, brake specific energy consumption, emission	R = 0.9926 R^2 = 0.9854, RMSE = 0.0048	GEP-based model robust enough to predict engine output
Safarian et al.[318]	ANN	Ash, moisture, volatile material, and fixed carbon, operational parameters	Net power output	R^2 = 0.999	ANN model exhibited agreement with observed data
Mutlu and Yucel[319]	Binary LS-SVM, multiclass RF	Biomass type, temperature	Syngas composition	Prediction accuracy (LS-SVM) = 96%, prediction accuracy (RF) = 89%	Binary LS-SVM superior to RF in prediction of syngas composition
Baruah et al.[320]	ANN	Biomass composition, reduction zone temperature	Producer gas composition	R^2 = 0.9991	ANN model exhibited agreement with observed data
Kargbo et al.[321]	ANN	Biomass composition, operating conditions	Yield and gas composition	R^2 > 0.992	ANN model exhibited agreement with observed data
Aghbashlo et al.[322]	ANFIS with PSO	Pyrolysis kinetics, process heating rate	Pyrolysis behavior	R^2 > 0.97	Lignocellulose pyrolysis behavior could be reliably estimated using ANFIS-PSO
Elmaz et al.[323]	Polynomial regression, SVM, ANN, decision trees	Waste composition, operating conditions	CO, CH_4, CO_2, H_2, higher heating value of output gas	R^2 > 0.9	MLP-ANN superior to other three machine learning techniques
Masoumi et al.[325]	ANN with PSO	Uncertainty in renewable energy system	Renewable energy allocation combined with battery energy storage	R^2 > 0.99	Metamodel of uncertainty in renewable energy and battery storage developed
Gayen and Jana[326]	ANFIS	Charging and discharging of battery storage system	Control of charging and discharging of battery storage system	R^2 > 0.9	ANFIS improved overall control capability

The challenges of modeling and simulation are briefly discussed in this section and how they may be overcome.

Data quality and lack of data, machine learning parameter tuning, technical infrastructure problems, lack of trained specialists, integration issues, hazards, compliance issues, and legal concerns are some of the bottleneck barriers to AI adoption in the smart energy sector.[327] Low-quality controllers, sensors, and controlled devices are used in energy system operation and data estimates.[328,329] The solution to most of the problems here can involve trained manpower from data collection to efficient modeling and result presentations. Data quality can be improved by the application of enhanced sensors and modern data acquisition systems. Technical infrastructure and integration require investments that are just a small fraction of renewable energy project costs.[330,331] Compliance and legal hurdles need implementation of long-term sustainable policy in this sector.[332] There may be challenges in this sector, but their mitigation can result in much more economic gains for the stakeholders.[333]

The shortcoming of adequate scientific focus while building more extensive integrated modeling systems sometimes makes integrating energy models challenging. Additionally, as energy systems grow decentralized, they become more complex and linked, relying on a variety of energy sources with increasingly interwoven boundaries. Because of these increases in complexity, certain existing energy models can no longer adequately address all energy optimization issues.[334,335] As a result, the complexity of the modeling domain in RSES must be addressed as soon as possible. Complex energy systems do not lend themselves to concise representations. As a result, the complexity of energy models in RSES is generally countered by the fact that the correctness of a model is determined by the basic assumptions incorporated into its design.[336] It was discovered that research on energy system modeling and simulation has continuously utilized modeling techniques with big data and hourly profiles of energy use, making RSES models challenging to solve in instances when substantial system and process data are not available.[337,338]

Many experts have a thorough understanding of technical issues. However, skilled people to create trustworthy AI-powered apps with real-world advantages are exceedingly difficult to come by. Even though power companies collect and retain data, it is difficult to digitize it with modern management software. Data loss, improper configuration, device failure, and illegal access are all risks that are linked.[339] The most significant impediment to the energy sector's modernization is outdated infrastructure. Utility businesses are currently engulfed in a plethora of data that they generate and have no clue how or when to deal with it. Despite having more data than anybody else, the data are scattered, unorganized, distributed across several formats, and kept locally. While the business makes a lot of money, it is also vulnerable to antiquated systems.[61,114]

It is evident from the literature that challenges and bottlenecks exist in effective implementations of machine learning methods in nanofluid-based renewable energy systems. However, ever-increasing computational power, the advent of intelligent machine learning techniques, and the availability of an AI trained workforce demonstrate the high growth aspect of this domain.[340] The voluminous research published in the last five years in various reputable energy journals substantiates this fact. The recently published literature review shows that researchers are meeting challenges in modeling complex energy systems with greater fierceness.

7. CONCLUSIONS

Several machine learning algorithms have been used in recent times to evaluate the performances of renewable energy systems working with nanofluids. This work focuses on a literature review to highlight current advances in machine learning research in the use of various machine learning algorithms for nanofluid-based renewable energy systems. Even though hundreds of archival papers are published on this subject each year, many essential elements, together with their nonlinear effects, complicate nanofluid research to new heights and restrict its practical usefulness. Surprisingly, sophisticated artificial intelligence has not been used to solve complicated challenges. Nonetheless, machine learning has the potential to be beneficial and cost effective in nanofluid research, enabling potentially dependable practice in solar collectors, solar-based desalination system, biomass gasification, wind energy, and PV/T systems. This review also acknowledges the increased application of the hybrid approach by combining the machine learning-based modeling and optimization approach in the last five years. Some noteworthy conclusions of this study are as follows:

(1) Several factors influence nanofluid thermophysical properties. Evaluating the thermophysical characteristics of various nanofluids across a wide range of parameters and flow conditions takes time and effort. Theoretical and empirical correlations may be quite ambiguous due to underlying assumptions. Many studies have shown that machine learning approaches like ANN can accurately predict nanofluid characteristics.

(2) Nanofluids improve heat transmission in renewable energy sources, including biomass, solar, geothermal, and wind. Machine learning approaches can accurately anticipate the performance of a renewable energy system based on nanofluids.

(3) The ANN and ANFIS predictions using modern commercial software are easy to implement and popular. The prognostic capability can be further enhanced using a hybrid approach with additional intelligent optimization techniques such as RSM, PSO, marine predator algorithm, genetic algorithm, swarm intelligence optimization, and more.

Newer ensemble machine learning algorithms, including boosted regression, K-means, K-nearest neighbor (KNN), CatBoost, and XGBoost, are gaining popularity due to their improved architectures and adaptabilities to a wide range of data sets. The ANN, ANFIS, and GEP techniques are mainly black-box methods, with the user having no idea how they work. This is a source of concern, and ethical artificial intelligence is required.

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■ ABBREVIATIONS

EG Ethylene glycol
Al_2O_3 Alumina
MWCNT Multiwalled carbon nanotubes
US EIA United States Energy Information Administration
RCSES Research Centre in Systems Ecology and Sustainability
ANN Artificial neural network
BP Backpropagation
GEP Gene expression programming
ET Expression trees
LS-SVM Least square support vector machine
QP Quadratic programming
RBF Radial basis function
SHC Specific heat capacity
MARS Multivariate adaptive regression splines
MSE Mean squared error
SCG Scaled conjugate gradient
MAPE Mean absolute percentage error
CNF Carbon nanofiber
LWLR Local weighted linear regression
RMSE Root mean squared error
SVR Support vector regression
STHEx Shell and tube heat exchanger
ELM Extreme learning machine
PM Particulate matter
WOA Whale optimization algorithm
NFs Nanofluids
ZnO Zinc oxide
ML Machine learning
SDGs Sustainable development goals
RE Renewable energy
MLP Multilayer perceptron
ANFIS Adaptive neuro-fuzzy inference system
GA Genetic algorithm
GP Gene programming
SVM Support vector machine
RNN Recurrent neural network
TC Thermal conductivity
GMDH Group method of data handling
MMD Maximum margin of deviation
RSM Response surface methodology
LM Levenberg–Marquardt
F-CNF Functionalized carbon nanofiber
PSO Particle swarm optimization
LGP Linear genetic programming
GPR Gaussian process regression
DPHE Double pipe heat exchanger
PHE Plate type heat exchanger
AQI Air quality index
NWP Numerical weather prediction
XGBoost Extreme gradient boosting

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