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Process modeling and parameter optimization of surface coatings using artificial neural networks (ANNs): State-of-the-art review

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ABSTRACT

Thin-film coatings and surface engineering procedures have a significant role in developing materials with extended mechanical, thermal and tribological properties. Advancement in the surface modification technology has encouraged investigators to develop new deposition techniques for producing high hardness, decent wear resistance, good corrosion resistance, high adhesion strength, and self-lubricating nature coated components. In this context, aiming desired level of such properties is key to successful performance of surface engineered coatings and their deposition methods. Parametric optimization and process modeling is a crucial step in the coating deposition process and for studying the properties attained for the coated components, but unfortunately it is not well understood in the literature. Although general, statistical and conventional approaches have been examined to model and predict the surface coating properties, there are still some challenges in outlining and comprehending the process parameters due to complex and non-linear nature of coating methods. Currently, machine learning techniques alternative to statistical approaches showing some sense of direction to address the quantitative gap between process inputs and outputs and build their relationship effectively. The review of this paper is primarily focused on providing a summary on artificial neural networks (ANNs) role in process modeling and parameter optimization of surface coatings. The present review can endow some knowledge to the researchers involving in this field of research.

1. Introduction

Surface engineering is the process of enhancing tribological properties of the materials by coating the surface of the components with other materials [1]. Thin-film coatings are playing a pivotal role in tribological applications in the modern engineering. These coatings have wide range of applications including machine elements [2,3], aerospace components [4], diesel engine piston rings [5], optical systems [6,7], solar cells [8], nuclear components [9], biomedical implants [10,11], food industry [12], pharmaceutical products[13] and especially, it has a greater importance in the field of manufacturing [14]. Mechanical and thermal properties like hardness, fatigue, abrasion resistance, permeation, corrosion, reflection, absorption, transmission, and electric behavior can be improved by using thin film coatings [15]. In addition to the above, coating the surface of the materials provides excellent tribological properties such as low coefficient of friction, lubrication and high wear resistance which eventually leads to exaggeration of life of the components. Emergence of surface engineering took place due to the challenges faced by many industrial systems in producing materials which can show high performance in different working environments. Mechanisms involving relative motion may require materials of high hardness, wear and corrosion resistance, dimensional and structural stability. For tribological applications, materials should possess improved tribological properties to withstand thermal and mechanical stresses in different environments [16].

Coatings and surface texturing were the two effective ways which were introduced to enhance the tribological properties of a material [17]. Depending on the thickness, coatings are of different types namely sol–gel technique, chemical bath deposition,

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spray pyrolysis technique, electroplating technique and electroless deposition. Low pressure chemical vapor deposition technique (LPCVD), plasma enhanced chemical vapor deposition technique (PECVD) and atomic layer deposition technique are the most popular processes which comes under chemical vapor deposition techniques. Vacuum thermal evaporation, electron beam evaporation, laser beam evaporation, arc evaporation, molecular beam epitaxy and ion plating evaporation are the techniques which uses evaporation as their source in the physical vapor deposition (PVD) process. Physical deposition techniques with the source as sputtering includes direct current sputtering (DC sputtering) and radio frequency sputtering (RF sputtering) [18]. High velocity oxy fuel (HVOF) coating, warm spray coating and cold spray coating are the deposition techniques where the thickness of the coated material is in the range of 70–1000 μm [19]. The most commonly used surface texturing methods are laser method, micro-EDM, ECM, CNC-ultrasonic sound, focused ion beam machining, AJM, vibro-mechanical texturing, micro-grinding, micro-casting and chemical etching. However, the role of coatings has increased rapidly in the recent years for improving mechanical, thermal and tribological properties due to their superior performance when compared to surface texturing methods [20,21].

H. Hoche et al. [22] investigated on application of PVD coatings for corrosion and wear protection of mild steel substrates and concluded that TiMgGdN coatings produced superior corrosion properties when compared to the industrial coatings. Y. Tian et al. [23] reported a study on the cavitation effect on behavior of corrosion of HVOF sprayed WC-10Co4Cr coating with post sealing in artificial seawater. C. Kainz et al. [24] demonstrated mechanical and microstructure properties of TiN/TiBN multilayer CVD coatings and observed that TiBN single layered coating has the highest strength and multi-layered TiN/TiBN coating is the hardest and toughest of the reported coatings. T.C. Chen et al. [25] presented a comparative study on the behavior of tribological properties of different thermal sprayed Inconel 625 coatings in a saline solution and deionized water. M. Lelis et al. [26] demonstrated the advantages of DC and RF magnetron co-sputtering processes in tailoring of TiO_2 film microstructure. Similarly, many studies were reported on different types of coatings and deposition techniques such as alumina coatings [27,28], magnetron sputtering process [29], thermal spray coatings [30–32], CVD coatings [33–35], PVD coatings [36,37], composite coatings [38] and electrostatic spray coatings [39–41]. In almost all the articles that were reviewed, process parameters played a crucial role in achieving deposition process efficiency. Researchers conducted numerous studies for determining the influence of input parameters on the process efficiency as well as comprehending the relationship between process input and output data.

Process modeling and parameter optimization have become the most important steps for attaining desirable properties of coated parts and as well as efficiency of coating deposition system. In this direction, many statistical, general and conventional techniques were introduced for parameter optimization in the deposition process. M. Ebrahimi et al. [42] applied response surface methodology (RSM) for determining the optimum deposition temperature and flow of hydrogen for producing diamond like carbon coatings (DLC) with low friction coefficient and high wear resistance. D.Z. Segu et al. [43] reported a study on application of Taguchi statistical techniques for studying the wear and friction properties of MoS_2 coatings on laser textured surface. A. Iwaniak et al. [44] applied ANOVA (analysis of variance) statistical technique for determining the effect of individual laser beam micro milling parameters on WC-CocCr coating deposited by high velocity oxygen fuel technique. Paturi et al. [45] applied finite element method for studying the application of solid lubricant coatings in machining operations and demonstrated its influence on tool-workpiece interface temperature and tool wear resistance. Y. Bao et al. [46] applied combination of monte carlo and discrete dipole approximation (DDA) for evaluating the radiative properties of TiO_2-pigmented coatings and ITO-pigmented coatings. Also, many studies were reported on application of statistical techniques in surface coating methods [47–51]. Even though statistical techniques were highly efficient in surface coating process modeling they have also shown some restrictions in handling large number of process parameters and in turn obtaining a judicious relationship between input and output data. Such difficulties were observed mainly due to the nonlinear and complex nature of surface coating methods and parameters involved in the process. Alternative to conventional and statistical approaches, machine learning techniques were introduced to model and optimize the process parameters in deposition processes [52,53]. Machine learning techniques which have the ability to solve intricate and nonlinear processes have attracted worldwide researchers to use them in the process optimization.

Different machine learning techniques such as support vector machines (SVM) [54], ANNs [55–57], genetic algorithm (GA) [58], ensemble method [59] and Gaussian process algorithm (GPR) [60] were opted by the researchers for process modeling in deposition technique process. However, the most preferred machine learning technique in surface coating method is ANN due to its capability of learning from the past data and using it to predict the response variable more accurately. More number of investigations were reported on application of ANNs in surface coating methods in the past couple of decades. T. Varol et al. [61] predicted thickness of coating in Fe-Al coatings fabricated by mechanical milling with the aid of neural networks. M.R.S Yazdi et al. [62] optimized coating parameters using ANNs for hardness of industrial tools. A.P. Plumb et al. [63] examined the influence of experimental design on modeling of tablet coating using ANN method. A. Godavarthy et al. [64] applied ANNs for studying the behavior of oxidation in composite boride coatings which are surface engineered by laser method. K. Bobzin et al. [65] optimized process parameters by correlating the high power pulsed magnetron sputtering plasma and coating properties using ANNs. J.E. Vitela et al. [66] modelled, predicted and analyzed the alkyd enamel coated properties using neural computing. ANN has shown high efficiency in optimizing the parameters and process modeling in surface coating methods [67,68].

There are no review reports in the literature that presents the importance and application of machine learning techniques in the surface coatings. Hence, summary on the role of ANNs in deposition processes is demonstrated in the present review to promote such robust machine learning techniques for process modeling and parameter optimization. Considering the certitude that parameter optimization and process modeling are the most pivotal steps in surface coating methods, the present review demonstrates the capability of ANN in producing the significant results in such complex nonlinear processes. Demonstrating such best machine learning techniques for the future use can lead to fundamental understanding of deposition process modeling and optimization.

2. Artificial neural networks (ANNs)

Computational systems which simulate the microstructure of a nervous system are artificial neural networks (ANNs). Structure of ANN is modelled in such a way that it resembles the human brain and the term ‘neural networks’ is also given after the word ‘neuroscience’. Functioning of ANN is a way similar to that of brain. Specific type of cell known as ‘neuron’ which provides the abilities like think, remember and learn from the past actions is the basic element of human brain. This neuron can connect with up to

200,000 other neurons for performing various operations. Generally, a neuron receives input from other sources and performs a nonlinear process by interconnecting with other several neurons and then gives the final result. Inspired by the functioning of human brain, ANNs are designed in a similar way for performing nonlinear and complex processes [69–71]. McCulloch and Pitts delineated the first formal model of a basic computing neuron [72].

Four basic components of a neuron are dendrites, synapses, soma and axons. Information is transmitted by axons from one neuron to several other neurons. Transmitted information is received at the synapses of the neuron. Number of neurons are formed into groups which are again organized into subsystems. A brain is an integration of these organized subsystems. Approximately, a human brain consists of 100 billion interconnected neurons. Fig. 1 shows the important aspects of human brain which were used to model an artificial neuron. Similar to human brain, ANN consists of group of interconnected neurons which interact with one another in a collective manner. In an artificial neuron, amassing of some potential takes place at the synapses which is known as connection weight or synaptic weight. Based on the required output, these weights are modified accordingly. Operations like summation of weights and defining the output of that neuron takes in an element which is defined as soma in biological neuron. Then the information is carried to other neurons by the axon [73]. Dendrites act as an input vector to excite and initiate the system to perform operations in the artificial neuron. Processing of given input in an artificial neuron can be observed from the Fig. 1.

ANN performs operations through connection of neurons in different layers. Basically, ANN is divided into single layered neural network and multi layered network. Multi-layered feed forward network (MLFFN) is the most preferred ANN model for various applications because of its high accuracy. Most of the articles reviewed in the present paper utilized MLFFN model for surface coatings applications. Generally, there are three layers in a multi layered neural network: input layer, hidden layer and output layer. Hidden layer may contain single or multiple layers depending on the given input size and relationship between input and response variable. Adaptable synaptic weights provide a direction for connection of each neuron in layer with other neurons of the previous layer. The knowledge acquired by each neuron is stored in the form of connection weights. These weights are modified in the training process using a required learning method. Before training, the weights are arranged in random manner and have no proper meaning whereas after training, they contain required information for producing the desired output. Initially the input is given to the network along with the output and parameters like learning function, transfer function, training function, number of neurons, number of layers and type of network are opted for optimization of the given input. Fig. 2. represents the processing of information from one layer to another layer in a MLFFN model.

From the Fig. 2, it can be observed that MLFFN model consists of input layer, hidden layers and an output layer. The weighted inputs are passed through the hidden layers and finally they are transferred to the output layer. Weighted set of inputs result is the output of each neuron. At summing junction, the sum of each weighted input is calculated by the below Eq. (1):

$$X = \sum_{i=1}^{n} (W_{ij}X_i + b_j) \tag{1}$$

N is the number of inputs (i = 0,1,2,3,4…… n), W_{ij} is the weight corresponding to given input X_i and b_j is the bias given along with the input and output which helps to fit the best model for the data [74]. Sum of weighted inputs is processed with the transfer function $F(X)$ and the output after processing is given by below Eq. (2):

$$Y = F(X) = F\left(\sum_{i=1}^{n} (W_{ij}X_i + b_j)\right) \tag{2}$$

Learning algorithms are required to obtain relation between inputs and outputs. There are several learning algorithms available for processing but the most opted algorithm is feed forward back propagation algorithm. A nonlinear transfer function is used to find the relation between input and output in back propagation learning algorithm. Sigmoid function is the most widely used nonlinear transfer function while designing the ANN network and it is given in the below Eq. (3):

$$F(X) = \frac{1}{1+e^{-x}} \tag{3}$$

There are two types of nonlinear sigmoid transfer functions used for finding the relation between input and output: log sigmoid (*logsig*) and hyperbolic tangent sigmoid transfer functions (*tansig*). Log sigmoid functions are defined by the Eq. (3) and *tansig* function is represented by the Eq. (4):

$$F(X) = \frac{1-e^{-2x}}{1+e^{-2x}} \tag{4}$$

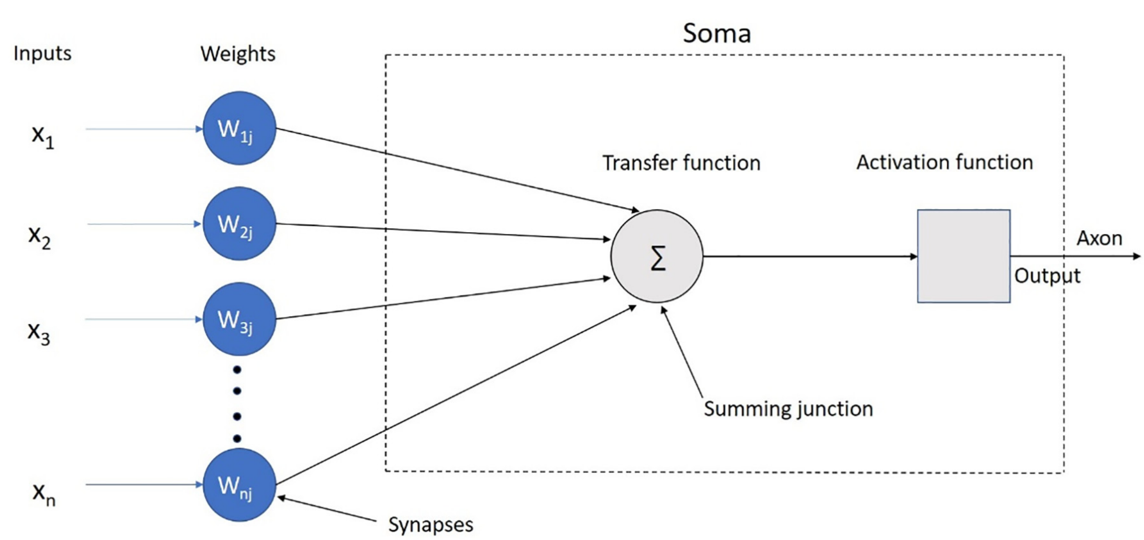

Fig. 1. Illustration of an artificial neuron model.

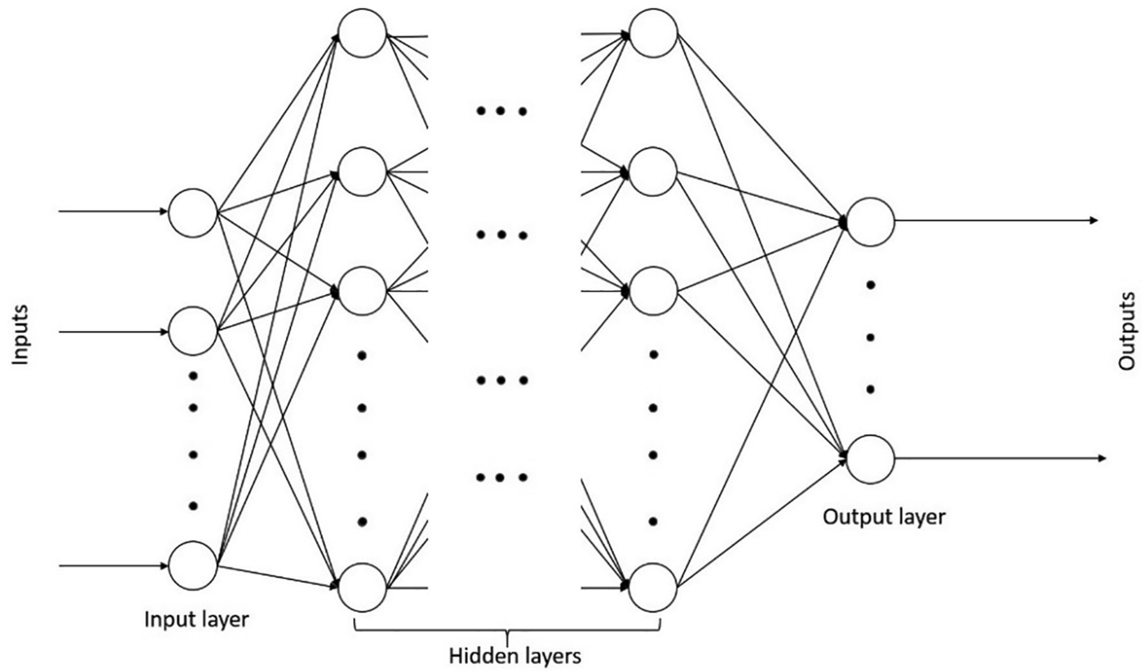

Fig. 2. Schematic diagram of multi-layered feed forward network (MLFFN) model.

Gradient descent weight and bias function (*learngd*) and gradient descent with momentum weight and bias function (*learngdm*) are the learning procedures used for training the given network. Parameters like momentum factor, learning rate, number of hidden layers and number of neurons in the hidden layers are selected for training the model. For performance evaluation, root mean sum squared error (*RMSE*) is calculated between the output and predicted values. After every iteration, ANN compares the predicted values with the given target values and calculates the error. If the error is greater than the prescribed error then it again runs the network by altering the weights in a direction of decreasing error. For avoiding the overfitting problem, the data is divided into training, test and validation data sets. Model is trained with the training data, test data is used to provide an unbiased evaluation of a best model fit on the training data. Finally, validation data set is used for performance evaluation and helps in avoiding overfitting problem [75–77]. The simplified ANN processing for producing desired output is shown in Fig. 3.

ANNs have the following features which helps to grapple with complexities such as nonlinearity and uncertainty:

- Learning from the train data to understand the given problem and finding the connections strengths which help in proper processing of the data.
- Highly applicable to systems where processing of large of inputs and outputs takes place.
- Determining the nonlinearity between the variables makes ANN highly suitable for model processing applications.

Being the robust technique, which helps in solving complex problems, ANN has found many applications in surface coating methods. Different applications of ANN in surface coating methods are presented in the study.

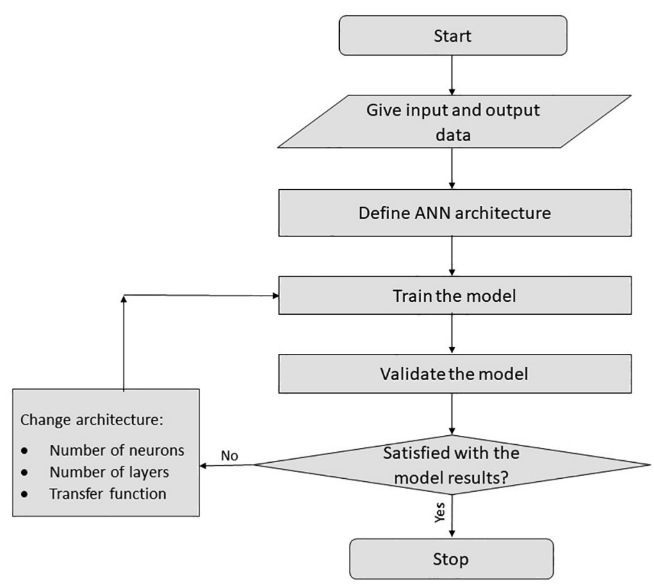

Fig. 3. Simplified processing of ANN.

3. Role of ANNs in surface coatings

Role of ANN in surface coatings has increased gradually over the past few years. ANNs have wide applications in surface coatings such as thickness prediction, prediction of hardness, microstructure analysis, prediction of tribological properties, quantitative analysis, process control, amphiphobic behavior, roughness, prediction of grain size, particle characteristics, predicting hysteresis effect in sputtering processes and oxidation behavior of coatings. ANN is playing a prominent role in process modeling of surface coatings by rejecting unwanted noises and compensating to the manipulated variables. They were able to optimize such complex nonlinear processes more accurately and were able to predict better conditions for depositing coatings on the surface of the material. To present their effectiveness in surface coatings, articles reported on different applications were reviewed in the present study. All the above-mentioned applications were reviewed to indicate the important role of ANNs in parameter optimization and process modeling of the surface coatings.

3.1. Thickness

Measuring the thickness of coatings is very essential to control the quality in surface modifications. Different applications of surface engineering are based on the thickness of coating that is deposited [78]. Therefore, it is important to utilize some advanced techniques to predict the thickness of the coating more accurately. ANN has been the best tool for thickness prediction in the recent years. Many investigations were reported on applying ANN in predicting the coating thickness. M. Barletta et al. [67] modelled electrostatic fluidized bed (EFB) coating process to predict the thickness trends with respect to time, voltage and air flow. The author has opted multi layered perceptron (MLP) neural network with back propagation algorithm for training the model. Genetic algorithm (GA) was also employed to enhance the capability of neural network model. The author was able to determine the best coating conditions for the EFB coating process by predicting the thickness at different values of input conditions. G. Khalaj et al. [79] predicted effect of different coating parameters on thickness of chromium carbonitride coatings on pre-nitrided steels using neural networks. The author has considered 17 different input parameters which are affecting the coating thickness and was able to determine optimum conditions for the coating process. A feed forward back propagation neural network model was opted and a correlation coefficient (R^2) of 0.9948 was obtained in predicting the thickness of coatings indicating a greater capability of ANN in nonlinear processes. T. Varol et al. [61] investigated the effect of milling speed, milling time and particle size on thickness of Fe-Al intermetallic coating with the aid of ANN technique. By modeling the process through ANN, the author could able to conclude that increase in milling time increased the thickness of coating. Satisfactory results were obtained through ANN process with mean absolute percentage error (*MAPE*) of 7.466%. S.K. Shukla et al. [80] developed an ANN model for predicting the thickness of Zn coating in hot dip galvanizing process. Considering 6 independent variables as input factors a 6-(9–6-1)-1 structured neural network was opted for predicted the thickness of the coating. High accuracy of ANN was observed with a maximum prediction error of 10%. Considering the performance of ANN in the above-mentioned studies it can be observed that ANN has been the major tool for the researchers for predicting coating thickness with high efficiency.

3.2. Hardness

Increase in hardness of the material makes the component highly resistant to wear. Coating the surface of the material by suitable deposition process is the most convenient way of increasing the hardness of the component. Predicting the improved hardness after coating the surface is the major tool for assessing the performance of surface coating method. Surface coating method is the complex process which needs advanced techniques that have the capability to understand such complex nonlinear processes and parameters involved in the process. To overcome such complexities, ANN has been the best option for the researchers to model and predict the coating hardness. A.M. Khorasani et al. [81] modelled CVD and PVD coating processes with the aid of ANN for predicting the hardness of titanium thin films. The author was able to predict the hardness of coatings with a 98.3% accuracy using a multi-layer perceptron neural network. It was concluded that using such predictive models for estimating the hardness can increase the material resistance against corrosion and erosion. It was also stated that the performance of the material can be improved by increasing surface hardness of the material. Model proposed by ANN has produced better results by increasing the performance and life of the cutting tool. M.R.S. Yazdi et al. [62] optimized coating variables for predicting the hardness of industrial tools using ANN approach. A significant improvement is observed by optimizing the coating variables using ANN method. It was concluded that the improvement of up to 16.75% of layers hardness can be accessible during titanium coating. M. Jiang et al. [82] applied ANN method for predicting the hardness of Ni-TiN nano coatings deposited by pulse electro deposition technique. Effect of different plating parameters such as TiN particle concentration, pulse frequency, duty ratio and current density on hardness of coatings is studied. Finally, optimum conditions for producing Ni-TiN nano coatings of greatest hardness were obtained with a maximum error of 1.03% using ANN method. D. M. Habashy et al. [83] modelled titanium dioxide thin film hardness using neural networks. It was concluded that, by applying ANN model, hardness of the thin film is predicted accurately with very high exactness when compared with the experimental data. Thus, a significant role of ANN is observed in predicting the coating hardness in the recent years.

3.3. Microstructure analysis

Microstructure features are directly related to the efficiency of the deposition process. Phase content, unmolten particle content and porosity levels are the most important features which must be controlled in order to maintain the high efficiency of the deposition process. Accurate prediction of microstructure features is necessary to enhance the performance of the deposition process. ANN, which has the ability to produce results with high efficiency can be the convenient technique for predicting the microstructure features. S. Guessasma et al. [84] developed the ANN methodology for analysing the microstructure features of atmospheric plasma process (APS) alumina-titania coating. The author has examined the effect of process parameters such as arc current, hydrogen rate and total plasma rate on the microstructure features like alumina phase content, titania phase content, porosity level and unmolten particle content. It was concluded that alumina and titania phase content are highly reactive to process parameters whereas porosity level and unmolten particle content are less sensitive to variation in the parameters. Alumina content has shown a direct proportionality nature with process parameters but other microstructure features exhibited an opposite trend with process parameters. In another study reported by S. Guessasma et al. [85], ANN approach was utilized to predict the porosity level in APS alumina titania coating. Optimal parameter combination was determined using ANN to maintain low porosity level. Parameters such as arc current, hydrogen ratio, total plasma rate, carrier gas flow rate and powder feed rate were given as inputs to the ANN to predict porosity level. Finally, optimal conditions for which low porosity level was observed were determined. It was concluded that increase in arc current and hydrogen fraction porosity level started decreasing whereas increased with respect to powdered feed rate. Parabolic relation was observed in total plasma gas flow rate and carrier gas flow rate. Main control factors determined with the ANN were arc current and hydrogen ratio. L. Wang et al. [86] applied back propagation neural network for building a nonlinear relationship between porosity and spray parameters in plasma spray process. Effect of different spray parameters on porosity of the coating was analysed using ANN method. A significant harmony was found between predicted results and the experimental data. It was stated that ANN approach can be an effective way to control plasma spray process and to optimize the performance of the coating. Thus, ANN has become a major source for analysing the microstructure features of surface coatings.

3.4. Tribological properties

Predicting tribological properties of the coated material is the main criteria for determining the effectiveness of deposited coating. ANN has been the best option for the researchers to predict the tribological properties of coatings. R.K. Upadhyay et al. [87] applied ANN for predicting the tribological properties of multilayer nitride films deposited by PVD technique. Total gas flow rate, bias voltage, velocity, lap, time and load were taken as the control parameters for the model. It was concluded that multilayer tungsten nitride coatings reduced friction and wear significantly. G. Zhang et al. [88] investigated wear and friction behavior of SIC-filled PEEK coatings using ANN method. The author has assessed the influence of sliding velocity and load on tribological properties of SIC-PEEK coatings. It was concluded that load larger than 9 N affected friction coefficient value significantly. An optimum condition where large load with intermediate sliding velocity reduced the performance of wear. H. Cetinal et al. [89] determined the amount of wear loss in Mo coatings deposited by APS process by subjecting to sliding wear against AISI 303 bodies under acid and dry conditions using ANN. The author could able to conclude that the wear loss is high in acid environment and the effect of load on wear performance is less when compared to that of in dry environment. K.L. Rutherford et al. [90] applied ANNs for determining the wear resistance of mono and multilayer TiN and NbN coatings deposited by PVD technique. It was concluded that more wear resistance and high hardness was observed in monolayer coatings and the coating with greater hardness and high wear resistance is found to be monolayer NbN coating. Increase in substrate bias increased wear resistance and by modifying the interface between layers by co-deposition improved wear resistance to a greater extent. S. Guessasma et al. [91] analysed the wear resistance of aluimina-titania coatings using ANN. The author was able to predict optimum parameter ranges for which high wear resistance is observed. By varying the process parameters, the author could be able to conclude that large parameter ranges do not produce significant results. Injection parameters and total plasma flow rate were used as control parameters for predicting friction coefficient of alumina titania coatings. With the help of ANN, variation of friction coefficient was predicted to be less than 10% with respect to process parameters. Similarly, many studies were reported to study the tribological properties of surface coatings using ANNs and concluded that ANN is much effective in optimizing process parameters for obtaining significant tribological properties of surface coatings.

3.5. Quantitative analysis

Even application of ANN in predicting the concentration of different substances in coatings has become quite significant in the recent years. L. Dolmatova et al. [92] applied ANN for quantitative analysis of paper coatings. The author predicted the concentration of styrene, butadiene and carbonate in the paper coatings. Both supervised and unsupervised learning with ANNs were opted for analysing the quantitative data of surface coatings. The author has concluded that accuracy of prediction in ANN is better than those of traditional methods. It was also stated that ANN helps to construct multivariate and multi-response models more accurately. They also determine an acceptable relation between inputs and outputs of a nonlinear process. W. Yating et al. [93] modelled plating rate and phosphorus content ($P\,\%$) in coatings of electroless nickel plating using ANN. The author predicted the effect of different parameters on phosphorous content and plating rate with a three-layered feed forward neural network with back propagation algorithm. After comparing the predicted values with experimental results, decent accuracy of ANN model was observed. ANN model could be able to find best combination of parameters for high plating rate and different $P\,\%$ in the coatings. M. Tatlier et al. [94] utilized ANN in predicting solution composition for the preparation of Na-alumino zeolite coatings. With the application of ANN, pure phase coatings were prepared from predicted solution composition and also, conducting number of experiments for discovering new synthesis compositions were decreased significantly.

3.6. Process control

Controlling the applied process is very crucial for avoiding unwanted noises and disturbances which may influence the efficiency of the method to a greater extent. Few investigations were reported by applying ANN for controlling the process and became successful by overcoming complexities in creating a control system for the process. E.V. Parfenov et al. [95] applied ANN for creating a control system for plasma electrolyte removal of titanium nitride coatings. With the application of ANN, the author could able to overcome inverse ill-posed problem in creating a control system. An inverse neural network has been employed for creating a control system where the different inputs were given at the output and the output was given in the input area. TiN coating has been successfully removed by intentionally changing the state of the surface using a control system modelled with the aid of ANN. G. Kimaev et al. [96] constructed a nonlinear predictive control model of a multiscale thin film deposition process using ANN method. ANN was successfully employed to obtain the optimum time varying profiles that would meet the required thin film properties. It was concluded that, observing the efficiency of computational technique, ability to reject unwanted noises and accuracy, ANNs can be used as a major tool for optimization and process control of multi scale process systems.

3.7. Amphiphobic behavior

Application of coatings which show the amphiphobic behavior has increased gradually over the years. In the areas such as aerospace, naval, mechanical, energy and marine, amphiphobic coatings usage has become prominent from the past few years. Amphipobhic coatings are considered as the innovative technical solutions for protection against surface wetting due to water and low surface tension liquid or fluids. However, predicting the amphiphobic behavior of coatings is also very essential for the successful application in different areas. ANN was applied in these coatings for predicting the behavior of coatings due its high prediction capability. N.V. Motlagh et al. [97] predicted amphiphobic behavior of flourosilica coated surfaces using ANN which was developed by heuristic methods such as genetic algorithm (GA), harmonic search (HS), simulated annealing algorithm (SAA) and gravitational search algorithm. Different models were compared with the neural network that were trained using particle swarm optimization (PSO) and concluded that the model trained by SSA presented more adaptive results than the other developed structures. Contact and sliding angles of different water droplets were predicted using ANN with a regression coefficient of 0.9979 and 0.9997 respectively. M.T. Gorjikolaie et al. [98] predicted wettability behavior of fluorosilica coated metals using ANN. For predicting the angles of liquid drops, ANN was developed by training the model using particle swarm optimization (PSA). It was observed that the obtained results from the developed models are highly accurate with a regression index of 0.9874 and 0.9920 for the contact angles and sliding angles respectively.

3.8. Roughness

For the prediction of proper wear behavior and controlling wear processes it is highly essential to understand the features of hardfacing surfaces. Generating models with systematic design and controlling the process in hard facing method is very essential to produce products with significant properties. Hence, ANN has been chosen as the alternative for conducting series of experiments to model the hardfacing process. M.D. Jean et al. [55] designed and developed ANN for depositing powders in coating treatment. Different process parameters were considered for predicting the performance of hard facing roughness of PTA coatings. A backpropagation ANN (BPANN) was opted to predict the hardfacing roughness of the PTA coatings. It was concluded that the contribution of hardfacing roughness to overall performance of coatings is 42.74% indicating that it is a highly implementing factor on performance of coatings. With the help of Taguchi orthogonal array different combinations of process parameters were obtained to use them as inputs to ANN for predicting the hardfacing roughness values. Average percentage error of 4.6% from the actual data is observed using ANN. M. Nalbant et al. [99] applied ANN for investigating the effect of cutting parameters, uncoated and CVD-PVD coated cemented carbides on surface roughness in CNC turning. Surface roughness values of TiN-coated cutting tool using CVD method, TiAlN-coated cutting tool using PVD method and AlTiN-coated cutting tool using PVD method are found to be the best when compared with uncoated cutting tool. With a R value of 0.99985 for the train data and 0.99983 for the test data, an acceptable accuracy was observed using ANN in determining the surface roughness value. G. Ohl et al. [100] studied the roughness values of TiAlN/Mo multilayer coatings using ANN. The predicted roughness values were compared with the Rutherford backscattering data of TiAlN/Mo multilayer coatings. Average absolute error observed in determining the roughness value using ANN was 0.3 nm. It was stated that ANN has shown excellent results in determining the roughness values from Rutherford backscattering data, which is a difficult task.

3.9. Grain size

To enhance the gloss of the surface, it is important to predict the grain size of the coating that is deposited on the surface of the material. For determining the effect of various parameters on the grain size of the coatings, ANN was chosen as the best tool by the researchers. A.M. Rashidi et al. [101] applied ANN to determine the effect of process parameters such as current density, saccharin concentration and bath temperature on the grain size of nano-crystalline nickel coatings. A feed forward multi-layered perceptron ANN was utilized to model the process. It was concluded that the current density and saccharin concentration are parameters which have significant effect whereas bath temperature has less impact on the resulting grain size. It was stated that the ANN model is a suggestable method for predicting the grain size of nano-crystalline coatings. A.S.M Jaya et al. [102] predicted the grain size of the TiN coating with the aid of ANN method. Considering the nodes in input layer as gas pressure (N_2), Argon gas pressure (Ar) and turntable speed (TT) and node in the output layer as grain size, different neural network models were developed. It was observed that 3–6-6–1 network structure has shown high accuracy of 96.02%. In the study, it was concluded that the ANN can enhance grain size prediction and has the ability to increase coated tool life in manufacturing process. L.A. Dobrzanski et al. [103] applied ANN for modeling of PVD and CVD coating properties. Investigation was performed to study the effect of different properties on the cutting tool coated using PVD and CVD techniques. From the study, it was concluded that the change in grain size significantly affected the stability of the blades and grain size is inversely proportional to the durability of the blades.

3.10. Particle characteristics

Particles characteristics are the most influencing variables on the performance of the coatings. It is important to have a proper understanding on the effect of different particle characteristics on the coating performance. Investigations were performed by applying the ANN technique for predicting the effect of particle characteristics on surface coating performance and a successful application of ANN is concluded by the researchers. C. Zhang et al. [104] studied the effect of hydrogen fraction on in-flight particles characteristics of APS 8 mol % Y_2O_3 – ZrO_2 electrolyte coating using ANN. With the application of ANN, it was observed that H_2 fraction has significant influence on particle temperature but has less impact on particle velocity. They concluded that the increase in particle temperature induced dense coatings and performance of gas-tightness is improved. T.A. Choudhary et al. [105] predicted the inflight particles characteristics of APS using ANN model. A multi-layered feed forward back propagation was employed to predict the in-flight particle characteristics such as particle temperature, particle velocity and particle diameter. Input power and injection parameters were considered as the inputs to predict the particle characteristics. The average relative errors obtained using ANN for particle temperature, particle velocity, particle diameter are 1.06%, 3.76% and 1.25% respectively. The study concluded that the ANN can be a best tool for achieving the desired process stability. A.F. Kanta et al. [106] established relation between process parameters, in-flight particle diameter and in-flight particle average velocity, surface temperature using ANN in plasma spray process. Successful application of ANN in establishing relation between in-flight particle characteristics and in-flight diameter for defined parameters was concluded in the study. Similarly, different studies were reported on the application of ANN in determining the particle characteristics [107,108].

3.11. Hysteresis effect

Deposition techniques like sputtering process exhibits hysteresis effect because of reactive gas flow. Major challenges were raised in preparing the non-stoichiometric compound films by sputtering process due to the hysteresis effect. Therefore, utilization of ANN in modeling the hysteresis effect in sputtering process has emerged to overcome the constraints for preparing the non-stoichiometric compound films. K. Danisman et al. [109] modelled the hysteresis effect of target voltage in reactive magnetron sputtering process using ANN technique. Considering the inputs as power level, reactive gas flow rate and its direction, an ANN model is created for predicting the target voltage in reactive magnetron sputtering process. Different training algorithms were selected to train various neuron models to study the hysteresis behavior of target voltage and based on the MSE of train and test data, BFGS quasi newton algorithm was concluded as the best neuron model for the process. Predicted target voltage values are very close to the measured target voltage values indicating a high accuracy of the neural network model.

3.12. Oxidation behavior

Oxidation reaction leads to high corrosion which deteriorates the life of the component. Protective coatings play a crucial role in controlling the high temperature oxidation. It is also important to determine the oxidation behavior of coatings to evaluate the coating performance. Various studies were reported on application of ANNs in prediction of oxidation behavior of coatings. A.M.

Table 1
Different applications of ANN in surface coatings.

S.No.	Author [references]	Application	Performance
1	T. Sahraoui et al. [112]	Tribological properties	Training error – 0.0186 Test error – 0.0180
2	E.M. Moser et al. [113]	Modeling the functional performance of coatings	Improved the functional performance of plasma polymerized thin films using general regression neural network (GRNN)
3	H. Wang et al. [78]	Thickness prediction	R = 0.9272
4	S.PR. Sahu et al. [114]	Tribological properties	Prediction error range – 0 – 10%
5	P.R. Pati et al. [115]	Tribological properties	Maximum prediction error – 6.248%
6	A.M. Rashid et al. [116]	Prediction of texture coefficient	R = 0.99
7	A.P. Plumb et al. [63]	Prediction of film opacity and crack velocity (pharmaceutical sciences)	Average relative error less than 10%
8	M.A.R. Mojena et al. [117]	Tribological properties	Mean squared error – 0.000689
9	B. Saleh et al. [118]	Erosion behavior	R = 0.99
10	K.R. Kashyzadeh et al. [119]	Thickness prediction	R = 0.9997
11	T. Sahinbaskan et al. [120]	Paper coatings (prediction of dry changes)	Mean deviation error – 0.4%
12	H. Salehi et al. [121]	Thermal barrier capacity of coatings	Maximum relative error – 3%
13	M.F. Tabet et al. [122]	Prediction of thickness and optical constants of coatings	Average predicted error = 0.0352
14	Chi-Yen Shen [123]	Prediction of thickness and optical constants of coatings	MAPE less than 2%
15	N. Kumari et al. [124]	Multi response optimization of ZnO thin films (thickness, roughness and optical transmittance)	R = 0.9998
16	Y. Xu et al. [56]	Erosion behavior of coatings	Mean square error – 3.35%
17	M. Ulas et al. [125]	Tribological properties	R = 0.9729
18	R. Hamzaoui et al. [126]	Magnetic properties of coatings	R = 0.99
19	W. Kwasny et al. [127]	Modeling the different properties of coatings	R (Erosion resistance) = 0.96R (Micro-hardness) = 0.92R (Roughness) = 0.95
20	B. Demirbay et al. [128]	Conductivity prediction of coatings	R = 0.9981
21	S. Genna et al. [129]	Thermal diffusivity of electro plated sample	Maximum deviation = 1.65%

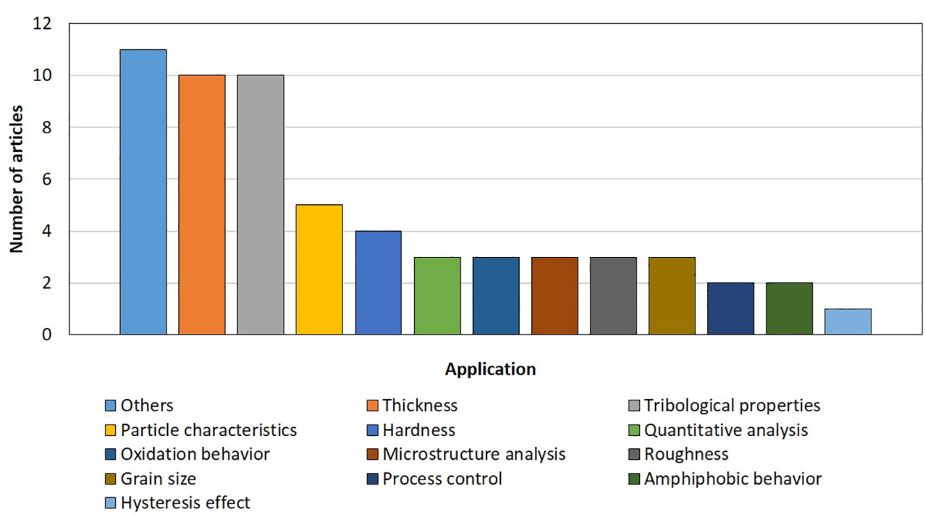

Fig. 4. Distribution of articles according to different applications.

Rashidi et al. [110] predicted the oxidation behavior of aluminized nano-crystalline coatings using ANN and high accuracy of the developed ANN model is concluded. A. Godavarthy et al. [64] applied ANNs in determining the mechanism and kinetics of oxidation in laser surface engineered composite boride coatings. S. Danaher et al. [111] examined the oxidation behavior of HIPIMS and PVD coatings with the aid ANNs and predicted the coatings with better corrosion resistance.

Similarly, ANNs have been widely used in other applications like predicting the thermal barrier capacity of coatings, optical constants (refractive index) of thin films, erosion behavior of coatings, prediction of texture coefficient, multi response optimization of coatings, film opacity and crack velocity (pharmaceutical sciences), magnetic properties of coatings, thermal conductivity and thermal diffusivity. Different applications of ANN in surface coatings are demonstrated in the Table 1. Distribution of articles based on the application in surface coating methods can be observed from the Fig. 4. Greater number of articles were taken from the thickness and tribological properties applications to demonstrate the significant role of ANN in those areas.

4. Conclusion

The present review emphasized on presenting the significant role of ANNs in surface coatings and its high capability in performing nonlinear processes more accurately. Surface coatings, where the process modeling and parameter optimization are the crucial steps for attaining the desired properties require robust techniques like ANN. Several applications of ANN are delineated in the present review to indicate how well a machine learning technique has been utilized for achieving the better performance in surface coating methods. In almost all the articles that were reviewed, feed forward neural network with back propagation algorithm has been employed for modeling the process. Even higher efficiency of ANN is observed in multi-response optimization of coatings indicating its versatility in operating. Since process of surface coating involves 35 to 40 input parameters, ANN has been the major tool for the researchers to model coating methods. ANN, which has the capability to perform such intricate nonlinear processes can be the best option for conducting further investigations on surface coating methods. In the literature, there is no such review that presented the crucial role of ANNs in parameter optimization and process modeling of surface coatings. Hence, this review can be a major source of information for the future researchers to accelerate in a particular direction for optimizing the parameters using ANNs in the surface coating applications.

CRediT authorship contribution statement

Uma Maheshwera Reddy Paturi: Conceptualization, Methodology, Writing - review & editing, Supervision. **Suryapavan Cheruku:** Formal analysis, Data curation. **Satwik Reddy Geereddy:** Visualization, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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