COMPUTER METHODS IN MATERIALS SCIENCE

2022, vol. 22, no. 4, 229–262
https://doi.org/10.7494/cmms.2022.4.0799

Computational intelligence based design of biomaterials

Arulraj Vinoth, Shubhabrata Datta*

Department of Mechanical Engineering, SRM Institute of Science and Technology, Kattankulathur, Chennai 603203, Tamil Nadu, India.

Abstract

This paper presents an overview of the applications of computational intelligence techniques, viz. artificial neural networks, fuzzy inference systems, and genetic algorithms, for the design of biomaterials with improved performance. These techniques are basically used for developing data-driven models and for optimization. The paper introduces the domain of biomaterials and how they can be designed using computational intelligence techniques. Then a brief description of the tools is made, followed by the applications of the tools in various domains of biomaterials. The applications range in all classes of materials ranging from alloys to composites. There are examples of applications for the surface treatment of biomaterials, materials for drug delivery systems, materials for scaffolds and even in implant design. It is found the tools can be effectively used for designing new and improved biomaterials.

Keywords: biomaterials, design, modeling, optimization, computational intelligence

1. Introduction

For millennia, materials have guided technological advancement. The naming of historical epochs, from the Stone Age through the Bronze and Iron Ages and into the current Silicon Age, reveals their significance in the development of human civilization. The origin of diversity in the material world is still largely unknown to the general public, but over the last 50 years, the understanding of the professionals and their control over the microstructures and properties of the materials has developed dramatically (Olson, 2000). This age, which we can call an Age of Design, will be characterized by the discovery of novel materials and methods of producing them. Materials design is obviously not a new idea. The need for innovative materials to meet the evolving demands of humanity has always been a struggle, as can be seen, if we only look back a few centuries to when materials engineering was first taking shape, perhaps under the names of metallurgy or ceramic engineering. Engineers and scientists have primarily relied on experimental testing in their attempts to produce novel materials. The majority of efforts to create new materials or enhance the qualities of existing materials by changing their composition and/or microstructure still use this strategy. This iterative approach to problem-solving is typically predicated on a premise. A hypothesis is developed based on assumptions about the experimental results. The observations that lead to a theory serve as the foundation for the inductive reasoning process that creates the hypothesis. With each new trial, successful or not, the observation becomes richer. As a result, the system is better understood and the hypothesis is given more and more specifics. However, the procedure is cumbersome, expensive, and time-consuming. The

* Corresponding author: shubhabp@srmist.edu.in
ORCID ID's: 0000-0002-8333-7391 (A. Vinoth), 0000-0002-7716-9205 (S. Datta)

criteria vary as quickly as the world around us in the modern day. It is the job of the materials scientist and engineers to provide the civilization with the needed materials (Pablo et al., 2014).

To reduce the time and cost for developing new materials, as per the requirement of the industry, computational materials science provides several tools for designing materials (Pablo et al., 2019). The science-driven models in different length scales can find the behavior of the designed materials from the atomistic level to the microstructure and even the product/component scale (Bhadeshia, 2008; Olson, 1997). Techniques like density functional theory and molecular dynamics are used by several materials scientists in the atomistic scale. Thermodynamic principles are used to model the phase transformation and microstructure designed. Different analytical concepts and numerical simulations are used to correlate the microstructure with the properties of the materials (Bozzolo et al., 2007; Koenraad et al., 2010; Raabe, 1998). All these tools can be integrated to develop a multi-scale materials modeling platform (McDowell et al., 2010). As the performances of materials depend on composition and processing, the manufacturing process also plays an important role for several important engineering materials. In such cases, integrating the processing parameters in the design process and thus incorporating the time scale along with the length scale becomes important. Integrated Computational Materials Engineering (ICME) tries to incorporate the tools like computational fluid dynamics or the kinetics of phase transformation into the materials modeling framework to approach the materials and manufacturing aspects together (Doghri et al., 2021; Yi Wang et al., 2019).

Now that experimental and characterization facilities in the materials sector have significantly improved, a large amount of data is being created globally. Yet until a relational connection is made, data is meaningless beyond its presence. Information is created from data in this relational database (Fig. 1). Nowadays, high-end computers and sophisticated software make it a relatively simple matter to accomplish this. The problem of knowledge extraction then arises. The true aim is to identify the inherent pattern of the relations in the data. The task might be greatly impacted by the strategy of data mining or knowledge discovery using statistical or computational intelligence approaches (Kalidindi & De Graef, 2015). The knowledge that was extracted might then be used to design materials with the requisite property or performance level. This materials design approach might easily reduce the risk of failure and save time and money. This method of engineering design is known as "materials informatics" in particular and "informatics-based design" in general (Liu et al., 2006; Rajan, 2005; Suh et al., 2006). The ability to design materials utilizing alternative methods of mathematical models created from the system's underlying physics or chemistry has been made possible by advancements in computational capability. Apart from scholarly curiosity, such efforts to create newer materials will undoubtedly intensify with time. The techniques for designing materials using such models are crucial for the future of material discovery.

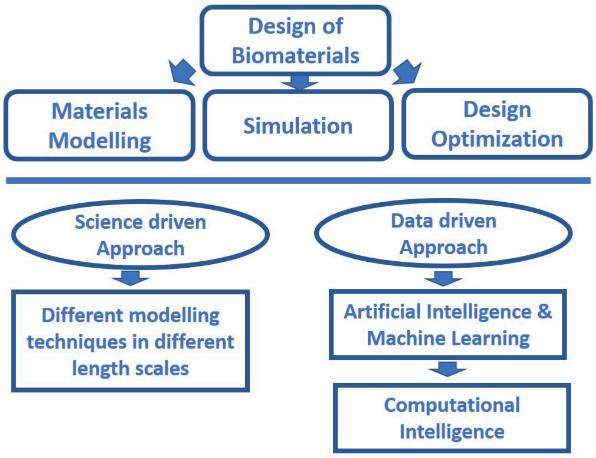

Fig. 1. Different strategies for computational materials design

Except for a few errant attempts, informatics-based design and mechanistic or physical model-based designs have been progressing together. The materials community feels there is a lack of science in the informatics-based approach because they rely on fundamental research for modelling. The section attempting to champion the materials informatics domain was unable to identify many applications of the alternative strategy. Each side has its own logic and is correct in its own way but this strategy will be fruitless. These two strategies must work together rather than against one another. The informatics professionals should first decide that it should only apply to systems for which ab initio or other physics-based techniques are impractical. The results of the materials informatics area should be seriously considered by the other group as well. Findings like these might result from the technique of knowledge discovery, helping to partially remove the restriction of physics-based models. The future of efficient materials design lies in the creation of hybrid systems that combine scientific and technological modelling. Artificial Intelligence and Machine Learning techniques should collaborate with other types of modelling in regions where knowledge is not accurate or just experimental observations are available. These models will improve the material design and might be more efficient than any of the individual approaches (Mueller et al., 2016).

Artificial Intelligence (AI) is the term used to describe the replication of human intelligence in devices that have been programmed to mimic human behavior (Yaghoubzadeh-Bavandpour et al., 2022). The phrase can also be used to describe any computer that possesses human traits like learning and critical reasoning. The ability of a system to effectively read outside information, to learn from it, and to use that learning to fulfil specific objectives and assignments through flexible transformation is described in a more detailed definition as AI. Older standards that labelled AI become obsolete as innovation advances. Because this objective is currently underestimated as a computers' capability, machines that develop requisite capabilities or detect text using model character identification are not now considered to exhibit AI. On the other hand, Machine Learning (ML) is a branch of computational science that developed from knowledge gathered in both computationally based AI concepts and the learning of data classification based on comprehension (Nilsson, 2005). Machine learning is just teaching computers to learn automatically from inputs without explicit programming. The word "learning" originated with humans and other animals. There are many similarities between animal and machine learning. Indeed, several machine learning techniques were developed to represent computational models of the fundamentals of animal and human learning. For instance, habituation is a fundamental academic practice in which an animal gradually stops responding to a repeated stimulus. The technique is finding newer applications in the domain of materials science (Schmidt et al., 2019).

According to the needs, AI uses a variety of computational techniques to describe the system. However, a considerable degree of uncertainty and imprecision must be accepted in order to search for and discover unknown correlations among the variables for a system not so specified, having complex and non-linear underlying interactions. Under these circumstances, Evolutionary Computation (EC), Artificial Neural Networks (ANN), and Fuzzy Logic (FL) are combined to form Computational Intelligence (CI) (Fig. 2). To make the CI family a little bit larger, occasionally a few additional computational tools are added. Such a suite of tools first appeared at the IEEE World Congress on Computational Intelligence in 1994 (in Orlando, Florida). Bezdek (1998) recommended defining a system as computationally intelligent if it solely works with numerical (low-level) data, contains a component for pattern recognition, and does not use knowledge as in the case of AI. Additionally, it must be computationally adaptive, fault resistant, have turnaround times that are nearly human-like, and have error rates similar to human performance. Another definition was developed by Eberhart & Shi (2007) in their book. They defined computational intelligence as a computing-based approach that demonstrated the capacity to pick up new information and/or deal with novel situations in such a way that the system was thought to have one or more attributes of reason, such as generalization, discovery, association, and abstraction. The description above makes it very evident that CI is a crucial tool for coping with uncertainty and complexity. The majority of real-world material systems are extremely complicated and challenging to model with standard techniques. Additionally, CI has the ability to identify and abstract knowledge, which is extremely significant from a design perspective.

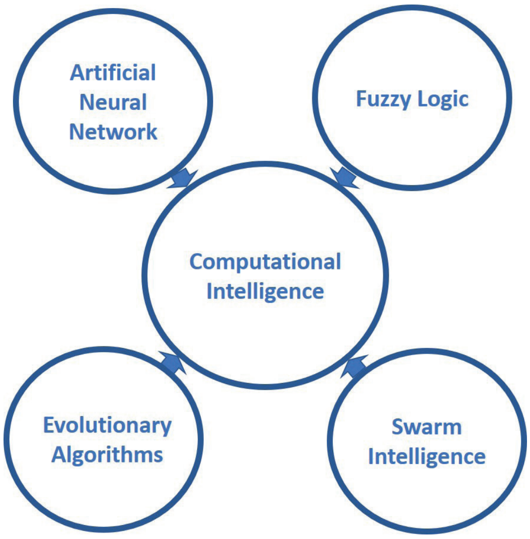

Fig. 2. Computational intelligence

Among the ML tools, arguably the most prevalent and effective technique is ANN, which draws its inspiration from organic nervous systems like the brain, and is able to create extremely nonlinear empirical correlations between the independent and responsive variables (Anderson & Rosenfeld, 1995). It has many interconnected, highly nonlinear processing units that are referred to as neurons. Instead of using the standard Boolean logic of "true" or "false", fuzzy logic (FL) computing is based on "degrees of truth" (1 or 0). Consequently, FL can be thought of as a superset of Boolean logic. Zadeh (1965) first proposed it in the 1960s as a way to simulate the ambiguity of natural language. In reality, fuzzy logic is a tool for creating solutions to issues where precision and relevance must be balanced. The Fuzzy Inference System (FIS) uses fuzzy logic and can successfully be applied to material systems, where it can make use of an imprecise understanding of a system. Optimization strategies are crucial for developing novel materials. When it comes to designing new materials, several evolutionary computing techniques, which are a part of the CI group of tools, such as differential evolution, genetic programming, and genetic algorithms, are becoming increasingly important. All of these techniques have adaptable methods for dealing with restrictions and objective functions. The Genetic Algorithm (GA), the first and best-known evolutionary algorithm, models Charles Darwin's idea of natural selection in order to find the best solution to a problem (Goldberg, 2002). GA is basically a stochastic global search approach that uses the survival of the fittest to try to evolve the optimum solution from a population of workable solutions that were first produced randomly. As in the case of other engineering materials, the expected behaviors of the biomaterials are multifaceted. In many cases, the requirements are conflicting in nature. In such cases, a multi-objective genetic algorithm (Deb, 2001) comes handy for designing such materials. All these tools in the CI domain are getting a huge application in the field of materials design and manufacturing process optimization. The tools are particularly efficient for handling a high number of parameters related in a highly complex and non-linear way within a materials system. To explore such hidden complexity of any materials system, to gather more information about the role of the parameters in constituting the final behavior of the material and finally to design materials with improved performance, these tools are found to be perfectly suited. Thus, CI techniques are also being applied quite extensively for designing biomaterials, while CI tools are being heavily used for designing materials (Datta, 2016; Datta & Chattopadhyay, 2013). Among all these techniques, ANN being the most applied modelling tool in materials engineering, the first comprehensive review on its application by Bhadeshia (1999) was published in 1999. Chakraborti (2004) has reviewed the applications of GA in the field of materials design.

The American National Institute of Health's definition of biomaterials as "any substance or combination of substances, other than drugs, synthetic or natural in origin, which can be used for any period of time, augments or replaces partially or completely any tissue, organ, or function of the body, in order to maintain or improve the quality of life of the individual" (Clinical Applications of Biomaterials, 1982) is the definition that is most widely accepted (Fig. 3). However, such a definition excludes items like surgical equipment and orthodontic braces (Bergmann & Stumpf, 2013). Gold and ivory were the first biomaterials used to replace cranial abnormalities. Romans and Egyptians both accomplished this. Since the 1900s, biological materials like placenta have been employed. The Williams Dictionary of Biomaterials (Williams, 1999, pp. 33–54) defined biocompatibility as the "ability of a material to perform with an appropriate host response in a specific situation". Celluloid was the first man-made plastic used for cranial defects, and polymethyl methacrylate was one of the first polymers accepted after World War II. Although this term initially appears unclear and useless, it constituted a huge advancement when it was originally introduced. Before this categorization, the general consensus was that successful materials mostly served as inert components of the body. For "successful" biomaterials, a large list of "non-properties" has developed, including nontoxic, non-immunogenic, non-thrombogenic, non-carcinogenic, etc. (Park & Bronzino, 2003; Ratner et al., 1996). The aforementioned criteria stipulated that materials must not only perform some function but also acknowledge that the interface they create with their introduction would cause a biological reaction. With the adoption of this concept, the notion that the substance might be really inactive was essentially discarded. The notion that a foreign substance could be inserted into our systems without triggering a reaction seems foolish given the level of awareness we have of our bodies as smart, complicated biological environments. Based on the tissue responses, it can be said that the biomaterials are those: a) which have a fibrous tissue layer between them and the bone tissue; b) having the ability to osseointegrate, or form chemical bonds with bone tissue, i.e. the implant surface is directly coated with the collagen and mineral phase of the neighboring bone; and c) under specific circumstances, it is possible to come into direct contact with the surrounding bone tissue when using bioinert materials, i.e. there must be no chemical interactions between the implant and the tissue (Yaszemski et al., 2004).

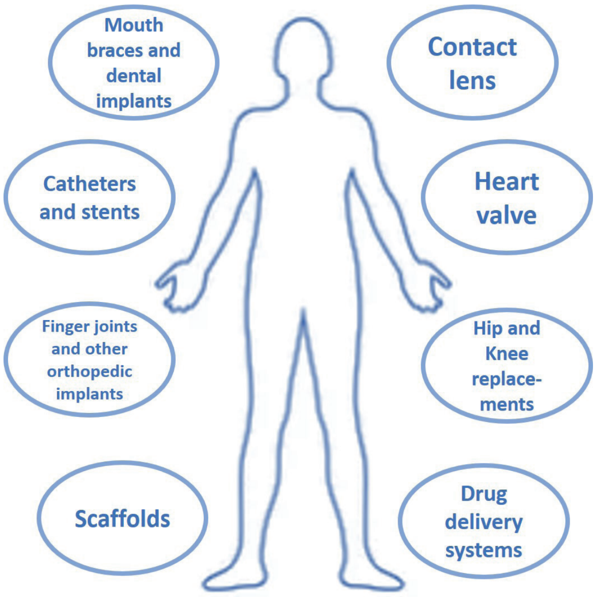

Fig. 3. Applications of biomaterials in the human body

In the case of biomaterials, like any other materials, the requirement for novel and improved materials is growing daily. Applications for tailored biomaterials with tunable functional characteristics range from drug delivery to regenerative medicine (Bryksin et al., 2014). Numerous design aspects and suitable models must be taken into account in order to increase the predictability of biomaterials performances. Gronau et al. (2012) in their review paper discussed the state of the art of synthesis and processing linked to the design of biopolymers, with a focus on the inclusion of bottom-up computational modelling. They evaluated the hierarchical structure and functional characteristics of three well-known biopolymers, viz. elastin, silk, and collagen. They found a lack of integrated approach of experiments and computation in designing such materials. A multiscale modelling in different length and time scales should be adopted to effectively approach the problem. The interaction between a cell and the biomaterial surface it grows on is still poorly understood, which makes it difficult to develop biomaterials suitable for therapeutic use. This surface communication can have a significant impact on cellular behavior, which in turn affects the likelihood that a material can successfully interact with the host tissue. In an attempt to explain the molecular mechanisms driving these cell-biomaterial interactions, transcriptomics data have previously been correlated with measures of biomaterial properties. However, because these multi-assay data are so complicated, they must be carefully and unambiguously characterized and stored, otherwise this could lead to the loss of important data or inaccurate data analysis. For this purpose, the Compendium for Biomaterial Transcriptomics (cBiT, https://cbit.maastrichtuniversity.nl) has been established as a publicly accessible resource, which may act as a platform for addressing such problems, and help in novel tailormade biomaterial development (Hebels et al., 2017). Using a web interface, users of the data warehouse known as cBiT can search through biomaterial-based transcriptomics data sets. Data of interest and related measurements of material qualities can be chosen and downloaded. Basu et al. (2022), in their review paper, acknowledged that the traditional methods for creating biomaterials and implants demand intelligent customization of process factors, protracted development times, and significant costs. Yet accelerating the manufacture of tailored implantable biomaterials and biomedical devices is essential to fulfil the biomedical and therapeutic demands of modern society. The data-driven design approach based on the Materials Genome Initiative was described by the authors as "biomaterialomics", which is nothing but the integration of multi-omics data and high-dimensional analysis with AI technologies throughout the full pipeline of biomaterials production. They opined that the fourth-generation biomaterials and implants, whose clinical performance will be predicted using "digital twins", will be developed using the data science-driven approach, which aims to bring together on a single platform the computational tools, databases, experimental methods, machine learning, and advanced manufacturing (e.g. 3D printing). The authors emphasized on the applicability of such approaches for three newly emerging research themes, namely patient-specific implants, additive manufacturing, and bioelectronic medicine. They highly advised that data science principles be taught to the new generation of researchers in addition to the greater adaptation of AI/ML technologies in biomaterials science. In another review paper, Russo et al. (2020) discussed how artificial intelligence and systems biology are being used in the design and development of vaccines. The authors felt that combining the two strategies will change healthcare by speeding up clinical trial procedures and cutting back on the time and expense associated with drug development and research. They examined the fundamentals of systems biology and artificial intelligence technologies used in the pipeline for developing vaccines. Though the vaccine is not within the domain of the present review, but the approach of amalgamation of data-driven modelling and system biology may be helpful for designing biomaterials too.

In the present review, primarily a brief description of the AI and ML techniques has been done with an emphasis on the computational intelligence tools. The next section deals with the applications of CI techniques in the different fields of biomaterials, starting with titanium alloys. Though among the metallic materials, stainless and Co-Cr alloys are also used as implant materials, but the research focus is more on the Ti alloys. Then such applications in the field of composite materials have been discussed. Then the coverage areas are applications in the fields of surface degradation and treatments of implant materials, materials for drug delivery systems, materials for scaffolds and finally, applications in the field of implant design. The paper is concluded with a discussion on the shortcomings of the present research and the future scope of applications of CI for better understanding and innovations of new materials to serve the area of health engineering to achieve a better life for mankind.

2. Overview of Computational Intelligence methods

Computational Intelligence methods involve a range of approaches, as mentioned above, each with distinct specialties in executing a certain task. The approaches and methodologies are described in this section. As the techniques are also included within the broader domain of AI and ML, the concepts of AI and ML are described first in brief, and then the CI techniques are described.

2.1. Artificial Intelligence

Artificial Intelligence (AI) is the recreation of human intelligence processes by machines which are built to think and act like humans. The phrase can also refer to every machine that demonstrates human-like characteristics like training and problem-solving. Often people think of robots the first time they hear the term "AI". It is because massive movies and books tell stories about machines that look like people and cause trouble on Earth (Shabbir & Anwer, 2018). But that couldn't be more far from the reality. AI aims at enhancing knowledge using a computer, rational thinking, and observation. The best thing about AI is that it can think and act in ways that gives the ideal opportunity to achieve a certain goal. A human way of thinking can be achieved in three ways: Self-examination – attempting to understand our individual thoughts, emotional experiments – observation of one's action and brain imaging – observation of brain's action.

AI operates by integrating huge data with rapid, repeated processing and advanced algorithms, enabling computers to automatically learn from patterns or characteristics in the data. The methodologies used in AI must be different. Trying to make a computer think like a human should be an integral part of actual science that relates to psychology, based on empirical evidence and hypotheses about real human thoughts and actions. On the other hand, a rationalist method combines elements of engineering and mathematics related to statistical data, control theory, and finance (Russell & Norvig, 2021). The two major classifications of AI are weak and strong artificial intelligence where the former involving a system to carry out only a specific task. All types of video games, Alexa and Siri are examples of weak AI. The strong AI system aims at carrying out any tasks similar to humans. Here they are automated to tackle situations which require a problem solving ability. Automated surgeries and Self-driven cars are examples of strong AI. AI is a vast research area that encompasses numerous theories, methodologies, and techniques, in among the primary subfields such as Machine Learning (ML), Neural Networks and Deep Learning which will be described in the further sections. AI is being applied in numerous applications. A few important applications in our day to day life as highlighted in Figure 4 involve health care, e-commerce, robotics, finance, facial recognition, marketing and social media etc.

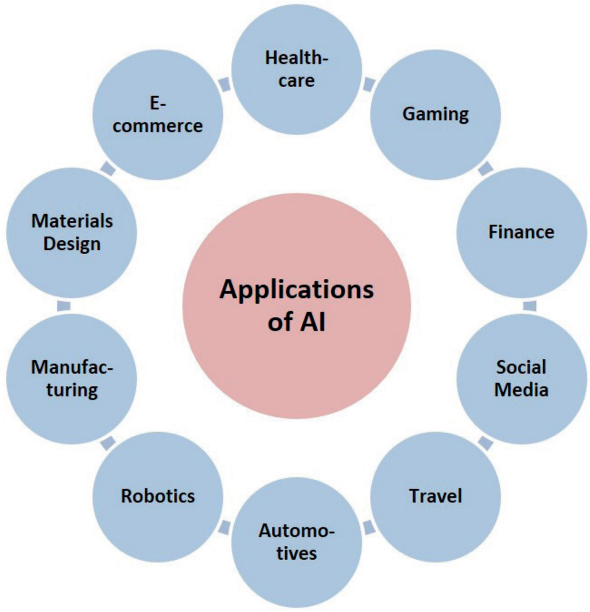

Fig. 4. Major applications of AI

2.2. Machine Learning

Machine Learning (ML) is a subfield of AI that progresses from the understanding-based learning of data analysis to the understanding of AI-based computational principles. Machine learning is the process of teaching computers to acquire knowledge automatically from their inputs without being explicitly programmed (Cielen et al., 2016). The concept of learning originated with both animals and humans. Machine learning and animal share numerous similarities. In fact, a significant proportion of machine learning techniques are derived from computational models of human and animal learning principles. Habituation is a fundamental scientific phenomenon in which an animal gradually stops reacting to repeated stimuli. Dogs are regarded as an ideal example of animal learning because they are capable of significant learning if they are taught to execute a variety of tasks, such as flipping over, eating, and collecting objects, etc.

Regarding the previous illustration of effective learning, it is only a couple of examples that exhibit machine learning in our modern day lives. Virtual assistants, traffic forecasts using GPS tracking, monitoring of surveillance cameras by AI to trace the crime or strange behavior of individuals, social networking sites utilizes ML for biometrics and news feed personalization, streamlining of search engine outcome, junk mail filtering where a machine memorizes all the previously labeled spam e-mails by the viewer, and a large number of other applications make extensive use of machine learning. All of these applications demonstrate that the integration of prior knowledge will favor the learning mechanism. ML is also strongly related to data science, through which it is acquainted with prediction-making (Langley, 2011). Anybody could wonder: "why must a machine learn something?". There are several reasons how ML is necessary. Essentially, it is just mentioned that the success of machine learning may help us understand how living creatures learn.

However, only a few key engineering aspects remain. Some of these functions cannot be described without an illustration; for instance, we may have the ability to recognize set of input/output, but not a clear relationship between inputs and desired outputs can be arrived. There are likely unknown correlations among inputs and outputs within a vast range of data. These correlations can be regularly shown by machine learning approaches. When is machine learning preferable to just programming a computer to accomplish a task? Complexity and the need for adaptability are two qualities of a problem that may need the use of programs that learn and grow based on their knowledge and learning. There must be tasks that are difficult to program, such as human actions such as driving, interpretation of images, and language processing of a person, etc., for which the field of machine learning (ML) relies on the idea of experience-based learning to provide acceptable outcomes (Shalev-Shwartz & Ben-David, 2013). The inflexibility of automated systems is a limitation; once the code has been developed and implemented, it cannot be altered. Nonetheless, many functions vary over time or amongst end users. For such situations, the usage of ML with encoding which decodes an existing source program by altering a fixed program to verify for differences in the writing styles of various users.

Though ML has proved revolutionary in some domains, ML programs frequently fail to achieve the intended outcomes (Dönmez, 2013). For example, in the year 2018, an Uber self-driven car was unable to recognize a pedestrian, resulting in his death (He, 2021). There are several reasons for this, including shortage of (appropriate) data, limited access to the data, bias of data, privacy issues, poorly selected tasks and algorithms, inappropriate tools and personnel, a shortfall of resources, and assessment issues. Machine learning is used in wide variety of applications. It has been seen that ML is a potential technology for the design and development of biomaterials for a variety of biomedical applications. For instance, in applying ML for the modelling and design of composite materials (Chen & Gu, 2019) that would change the design and optimization of composites for the forthcoming era of materials with remarkable properties.

2.3. Metaheuristic optimization

Optimization is a common practice in daily life. We employ it knowingly or unknowingly for the majority of our daily activities. When we attempt to do a professional task with less work or time, we are engaging in an optimization technique. Amongst various optimization methods, the conventional derivative-based methods were the most well-established and prevalent. Any optimization algorithms are broadly classified as heuristic and deterministic algorithms. Deterministic algorithms emerge with a clear relationship between the characteristics of the system. When the relationship between the system attribute and the fitness or objective of the system is intricate or ambiguous, it becomes difficult to tackle a problem probabilistically. A heuristic algorithm (Michalewicz & Fogel, 2004) collects information about the system, tests the fitness of the randomized solution, and determines the next solution to generate. Therefore, these methods rely on the nature of the issue. A metaheuristic technique, on the other hand, mixes heuristics with the objective function without regard to the problem's structure (Blum & Roli, 2003; Glover & Kochenberger, 2003). Thus, a metaheuristic algorithm broadens the applicability of heuristic methods to a variety of issues. Metaheuristics can locate high-quality solutions to problems of combinatorial optimization in an acceptable amount of time (Dhiman & Kumar, 2017).

In recent years, however, the introduction of metaheuristic optimization techniques has altered the optimization domain and made these techniques more popular due to their capacity to tackle complicated problems and reduced likelihood of becoming stranded in local optima (Datta et al., 2019; Halim et al., 2021). A metaheuristic technique includes the strategy of guiding and modifying pure heuristics to develop solutions that surpass those generated by heuristic methods. The metaheuristic optimization approaches can be classified into three distinct categories. The first group comprises evolutionary computation, which includes evolutionary strategy, genetic programming, differential evolution, genetic algorithm etc. The second group is the swarm intelligence group, which includes ant colony and particle swarm optimization techniques and so on. These two classes of techniques are also known as biologically inspired optimization methods. The third group comprises of optimization methods influenced by physical processes, with simulated annealing being the most prevalent technique in this group. The classifications of metaheuristic algorithms are depicted in Figure 5. A few of these methods will be explored later in the further sections. The versatility of metaheuristic algorithms to address situations with multiple objective functions and restraints is greater. This has increased the application of these methods to different fields of study, especially in the design of materials.

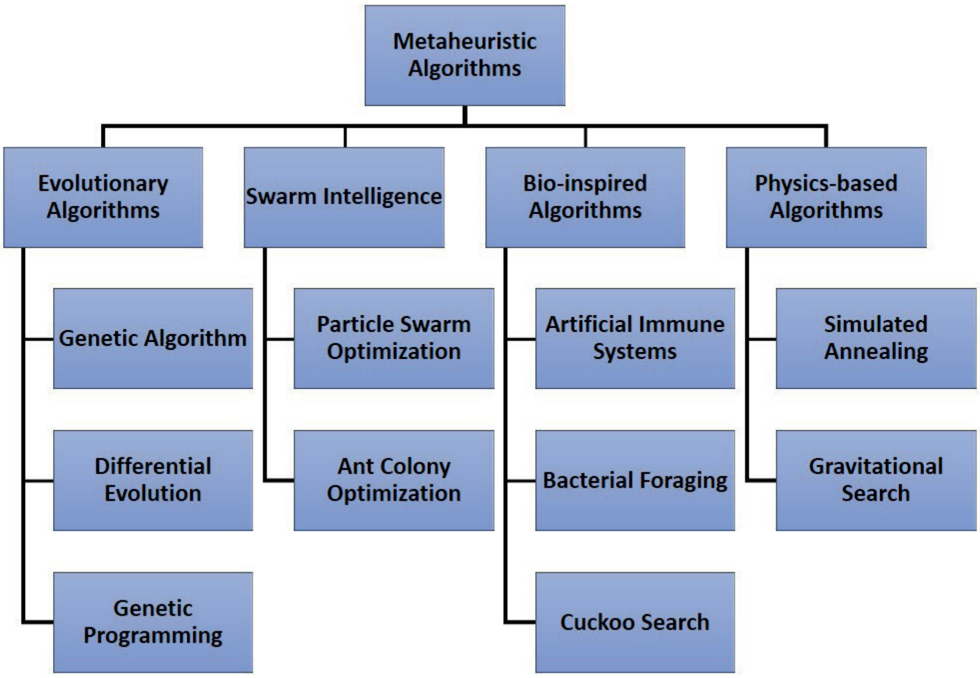

Fig. 5. The popular classes of metaheuristic algorithms

2.4. Computational Intelligence

The term Computational Intelligence (CI) is the study of evolutionary mechanisms that permits or assists intelligent behavior in challenging and dynamic situations. It comprises a subset of AI. These mechanisms consist of AI paradigms that are capable of learning or adapting to new contexts, as well as generalizing, abstracting, discovering, and combining. The CI models that are covered are as follows: Artificial Neural Networks (ANN) and Fuzzy interface systems (FIS) along with optimization tools like Genetic Algorithm (GA) and other evolutionary and swarm intelligence based algorithms. Specific methods from such CI models have been successfully implemented to tackle real-world issues, but the recent trend is to construct hybrid models, as no single model is preferable in all circumstances. Thus, researchers leverage the unique strengths of the hybrid CI models and eliminate their respective deficiencies. All of the CI models originated from biological systems. ANNs mimic biological neural networks, GA mimics the natural genetic evolution and FIS was derived from research into how species react to a different environment.

2.4.1. Artificial Neural Network

The Artificial Neural Network (ANN) approach has recently emerged to be particularly beneficial in the field of computational materials science for resolving complicated nonlinear problems. It is a data information handling system that is cognitive and reliable, and it can represent complicated and complex situations. Despite of regression analysis, the ANN technique offers adaptation, learning, and prediction capabilities, resulting in superior predictive accuracy. The core benefit of a neural network model is that it can learn from experiences and understand trends in a sequence of datasets containing input and output parameters without making any assumptions about one's nature or interrelationships. Any mathematical relations are not required for this model (Kurt & Oduncuoglu, 2015). ANN's inherent feature allows them to uncover more complicated correlations in datasets than traditional models. An Artificial Neural Network (ANN) is a data handling model based on how biological neurons, such as the brain, that process information (Mukherjee & Singh, 2009). It is made up of a vast number of extremely interlinked processing units called neurons that work together to solve issues. ANN is designed for a particular problem such as object recognition, clustering, or predictive learning. In biological systems, learning entails adjusting the synaptic connections that arise amongst neurons (Anderson & Rosenfeld, 1995; Gurney, 2018). Every neural network has a number of processing elements that get inputs from the outside environment, which are termed as "input layers" or "input nodes" respectively. It does, however, have one or even more hidden layers that only take inputs from some other processing elements. The 'output layers' are a set of processing elements that indicate the eventual outcome of the neural network algorithm (Ganguly et al., 2016). In general, an artificial neural network (ANN) trains from experiences and detects correlations in a collection of input and output units deprived of coming to any conclusions about their type or interrelationships (Mandal et al., 2009).

Figure 6 shows the architecture of an ANN with a typical feedforward network, which is used in this study with three different interconnected layers as input (x), hidden (H_j) and output (y) layers (Prajapati & Tiwari, 2017). Each layer is linked using transfer functions. Tan hyperbolic (tanh) non-linear transfer function is used to link the input (x) and hidden nodes (H_j) which are articulated in Equation (1) involving the weighted sum of the normalized inputs (x_i) with the connection weights (w_{ji}) that connects the input to hidden layers with the addition of its corresponding layer's bias values (b_j).

$$H_j = \tanh\left(\sum_j w_{ji} x_i + b_j\right) \tag{1}$$

The linear function is used to determine the output node (y) by a weighted sum of the outputs with the connection weights (W_j) of hidden to output layer with the addition of its corresponding layer's bias values (b') is articulated in Equation (2):

$$Y = \sum_i W_j H_j + b' \tag{2}$$

By adjusting the weights w_{ji}, w_i in Equations (1) and (2), different outputs can be obtained. The network is "trained" on a collection of data related to input–output that are normalized to obtain the best values for these weights.

To do so, first normalize the input–output data in the range of −1 to +1 using Equation (3).

$$x_j^N = \frac{2(x_j - X_{\min})}{X_{\max} - X_{\min}} - 1 \tag{3}$$

Where x_j^N is the normalized value, x_j is the input or output parameter, and $X_{\max}$ and $X_{\min}$ are the upper and lower bounds of the corresponding parameter. By modifying the weights w_{ji}, the network can be trained to reduce an error function that would be essentially a normalized total of squared errors. As a result, an ideal representation of the input–output correlation emerges.

The backpropagation (BP) algorithm is created to handle the issue of finding connection weights for a multilayered ANN with feed forward linkages from the layers of input to the hidden and finally to the layer of output. The approach is a gradient algorithm in iteration (Ding & Chen, 2005) that aims to reduce the squared error between the expected and actual output. The BP learning method is depicted schematically in Figure 7.

ANN is a type of machine learning system that more precisely maps the existing input–output correlation. It can take into account the nonlinearity of the correlations between the variables.

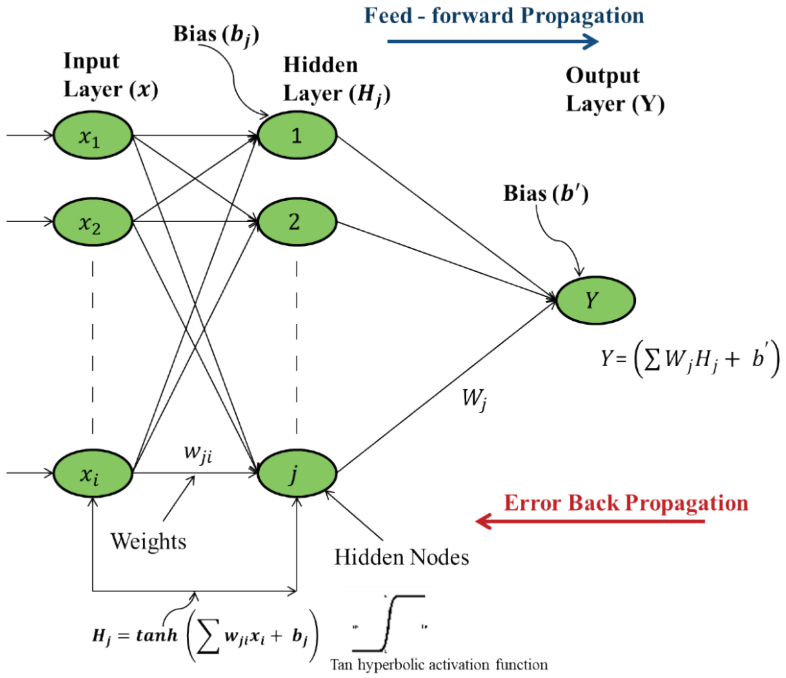

Fig. 6. Configuration of ANN (Arulraj et al., 2022)

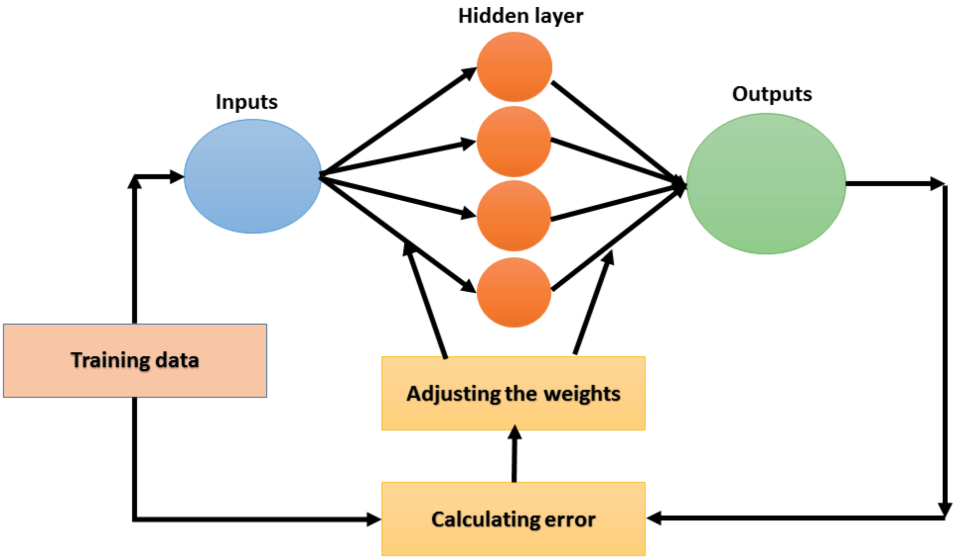

Fig. 7. Schematic of backpropagation in ANN model

This technique has been proven to be highly suitable for estimating the tribological and mechanical characteristics of composites, which are proven to be reliant on a set of multiple input variables when combined with the BP algorithm (Datta & Banerjee, 2006). In situations where establishing a physical model is challenging, neural networks can be used both successfully and efficiently.

2.4.2. Fuzzy interface system

Fuzzy logic is a specialized version of the traditional (Boolean) theory that accounts for inconsistencies in data and imprecision in knowledge. In the 1960s, Dr. Lotfi Zadeh introduced it as a way to simulate the uncertainties of natural language. Furthermore, the range of applications grew to include consumer devices, electrical equipment, automobiles, and highway monitoring systems (Zadeh, 1965, 1988; Zedeh, 1989). A fuzzy set is one whose boundaries are not sharp or well defined. As seen in fuzzy logic, the truth of every given assertion is a question of degree; the set includes components with only a level of membership. A membership function maps the membership value (or levels of membership) of every point in the input space ranges between 0 and 1. The structure of the curve of the membership function can be described as a value that corresponds to the system's specification in terms of clarity, accessibility, performance, and efficiency. The basic membership functions are straight line functions including the trapezoidal and the triangular, which is most commonly used.

Fuzzy linguistic characterizations are conceptual representations of systems created by fuzzy if–then rules articulated as:

$$\text{IF } (x_1 \text{ is } A_1, x_2 \text{ is } A_2, \ldots, x_n \text{ is } A_n) \text{ THEN } (y_1 \text{ is } B_1, y_2 \text{ is } B_2, \ldots, y_n \text{ is } B_n)$$

where x_i and y_j are the linguistic variables corresponds to the fuzzy sets A_i and B_j.

The FIS is depicted in Figure 8 as having three components: a fuzzifier, an inference system with a fuzzy rule basis, and a defuzzifier. Fuzzification aims to translate inputs to values between 0 and 1 using a collection of membership functions of inputs. The fuzzy rules are used to provide fuzzy outputs for various rules. The results are subsequently blended to provide fuzzy output dispersion. There are numerous fuzzy combination strategies that are not mentioned here. Generally, fuzzy combinations are referred to as "T-norms". In many circumstances, it is desirable for a FIS to produce one crisp output. This number is obtained by a technique called defuzzification. Several strategies are also offered for defuzzification.

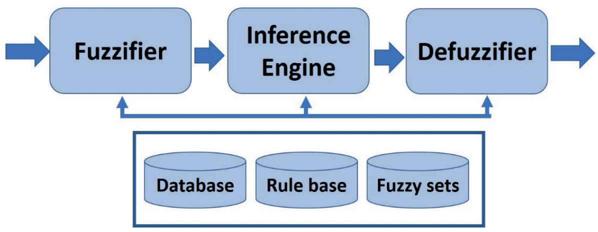

Fig. 8. Schematic of FIS

Mamdani (1977) and Sugeno (1985) are two of the most prevalent forms of FIS. Contrary to the Mamdani FIS, the Sugeno FIS does not compute the output implication by clipping the membership function of the output by the rule severity. In fact, there isn't any output membership function in the Sugeno FIS. Rather, the output is a number that is calculated by the product of each input by a constant and then adding the results. As is obvious from the preceding description, FIS is appropriate for modelling systems in which, on the one hand, imprecise information is communicated in a logical if-then rule fashion rather than via expression, and, on the other hand, data are unavailable for constructing data-driven models such as ANN. This is a common occurrence in complex and evolving material systems. Nonetheless, the efforts performed in the area of materials modelling with FIS are not yet noteworthy.

2.4.3. Genetic Algorithm

Genetic Algorithms (GAs) involve biologically based computing techniques, which act according to the concepts of Darwinian natural selection theory. Most of the studies involving engineering optimization find it to be a fit one as the method is highly effective. Thus GA is a hunting technique founded on selection via nature and ideologies of natural genetics so as to arrive at the finest result for any definite problem (Deb, 1995; Kramer, 2017). GA focuses on feasible solutions population so as to bring out superior approximations for a specific solution by using the concepts of survival of the fittest. By selecting individuals as per their fitness level and mating them collectively, a new collection of solutions is generated with each successive generation. Similar to natural adaptation, this process results in the evolution of individual populations that are more adaptable to their environment than their ancestors. In genetic algorithm (GA), a probable solution to an issue is encoded as a set of variable strings known as chromosomes. A single chromosome is regarded as a unique solution, and a huge population of solutions with random parameter values is generated.

Breeding involves two operators, namely crossover and mutation. Crossover facilitates basic biological cross-fertilization and mutation implies noise introduction. To obtain remarkably good results for a range of problems, one needs to apply these operators in a simple manner with the aid of a rational mechanism of selection. Crossover and mutation are followed by the assignment of fitness values to individuals. Thereafter the individuals are selected for the process of mating, considering their respective fitness levels backed by objective function evaluation which is continued via successive generations. Individual's performance may be enhanced in this manner by way of preserving good individuals to be cross bred. The individuals that are less fit eventually die out in the process. Upon satisfaction of some criteria, the GA method is concluded. i.e., after attainment of a specific point in the search space, or after a said amount of generations, and a mean deviance in population. It is significant to notice that a range of prospective solutions are derived for any given problem by GA and there are options for the user to elect from. GA helps in the simultaneous identification of substitute solutions in scenarios wherein any specific problem does not have a single possible solution just as in the case of a multi-objective mode of optimization.

The representation in Figure 9 highlights a simple genetic algorithm (SGA) structure as per Goldberg's description (Datta & Chattopadhyay, 2013). GA initializes a random population comprising potential solution points called individuals in the first step. It is decided first if the individual can be deemed good or bad for the given problem, depending on the fitness obtained from objective function evaluation. After evaluation and assignment of fitness value to each individual, the first genetic operator namely the selection process and the initial population meet. This operator increases the probability of survival for strong individuals while degrading the fitness of the weakest. Following that, the crossover operator is used to a subset of individuals in order to create new individuals by combining the current ones. Crossover occurs as a result of reproduction and permits two individuals to swap structures based on the probability factor. As a result, a pair of offspring solutions have been created; each with the qualities of their parents (Booker, 1987).

The mutation operator is then used to provide population diversity. Because a population's fitness may remain stable for several generations before a superior individual is discovered, standard termination criteria become difficult. A frequent technique is to end the GA after a predetermined amount of generations and for comparing the quality of the population's best members to the problem criteria. If no satisfactory answers are seen, the GA shall be repeated or a new search with a larger number of generations is initiated.

Many optimization challenges in the real world involve numerous conflicting goals. During multi-objective situations, one of the methods is genetic searching based on the principle of Pareto optimality (Deb, 2001; Deb et al., 2002). Having many contradicting objective functions, the idea of 'optimal' is embodied by groups of solutions that provide the best feasible tradeoffs between the objectives. These solutions are known as the Pareto, as opposed to the global optima utilized in problems with single-objective. The mere meaning of Pareto optimality necessitates that no alternative conceivable solution could be at least as good as a part of the Pareto set with regard to all outcomes, and strictly better with regard to at least one. Numerous multi-objective genetic algorithms have thus far been presented based on selection procedures that employ the principle of non-domination.

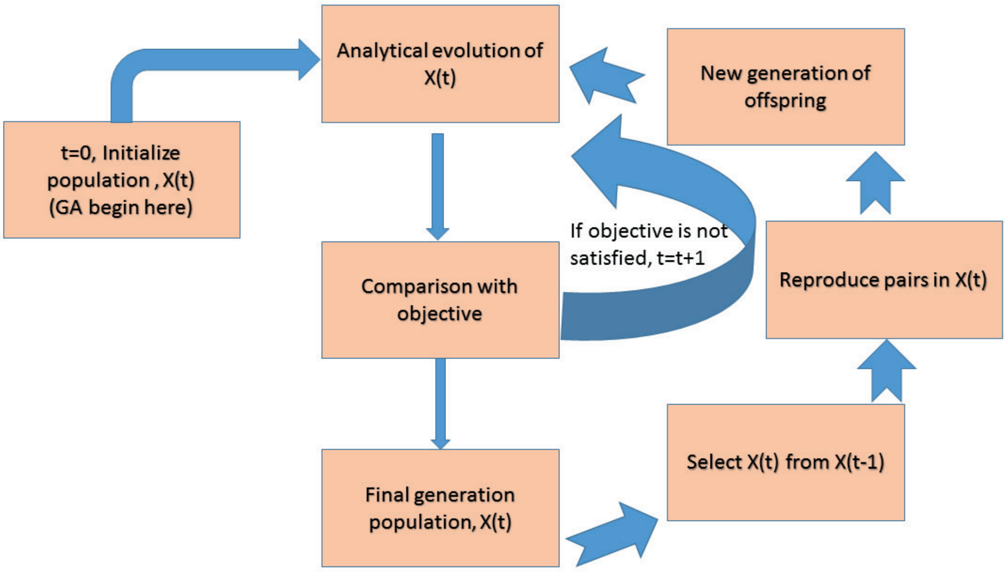

Fig. 9. A schematic representation of a simple genetic algorithm

2.4.4. Hybridization of ML using evolutionary algorithms

Several researchers (Chakraborti, 2022; Giri et al., 2013b; Hariharan et al., 2014; Roy et al., 2020) have attempted to use different hybrid ML models and evolutionary algorithms for solving various multi-objective problems. A few hybrid models are Predator–Prey GA (PPGA) and ANN, Evolutionary Neural Network (EvoNN), Bi-Objective Genetic Programming (BioGP) and Evolutionary Deep Neural Network (EvoDN). EvoNN was established to use the evolutionary algorithms in a multi-objective fashion on a population of NNs in order to avoid the issue of underfitting and overfitting in the conventional NN (Chakraborti, 2016; Pettersson et al., 2007). The ANN models produced by EvoNN have just one hidden layer. This is expressed as **a** × **b** matrix in the EvoNN method, where **a** is the amount of input nodes and amount of output nodes as **b**. To hold bias values, an additional row is introduced. A population of ANNs can be created by stacking together these new 2-D matrices. A neural network with many hidden layers and various numbers of nodes in each layer is created using EvoDN (Roy & Chakraborti, 2022). Each layer typically has a varied number of connections; hence they can't be expressed by identically sized 2-D matrices. The programme groups the weights and biases of similar layers from the entire population together within 3-D matrices as before to get around this problem when processing the full population, and then groups the numerous 3-D matrices clubbed in a cell structure. This makes manipulating and handling the populace simpler. The BioGP method (Giri et al., 2013a) uses a single objective optimization method to reduce prediction error at first, and a bi-objective optimization scheme based on GA to find a balance between accuracy and complexity. An advantage of the BioGP method is that it acts as a decision maker which freely chooses the mathematical processes necessary to build a meta-model. EvoNN and BioGP both use the Predator Prey Genetic Algorithm (PPGA) as its foundation. Predator-prey GA often imitates the biological conflict that exists between different species in a natural forest. The natural occurrence of predators seeking their prey in a forest served as the model for the predator-prey GA (Deb et al., 2019). As a result, the stronger prey survives while the weaker ones are more likely to be killed by the predators. The potential solution set in this case is represented by the prey population.

3. Applications of CI in the design of bio-materials

The following discussion aims at the use of CI approaches for the design of bio-materials with superior performance properties.

3.1. Titanium alloys for hard tissue implants

Titanium (Ti) alloys are the most prominent biomaterials for a wide variety of biomedical applications mostly in the domain of dental and orthopedic implants. The main advantages of Ti alloys are their high specific strength, low corrosion resistance and adequate biocompatibility. In the case of hard tissue impacts, the elastic modulus of the implant materials should be as close as possible to the modulus of the cortical bone to avoid stress shielding in the adjacent bones. Low modulus Ti alloys with high strength for bio-compatible implants are much needed in optimal values of alloying elements. Utilizing CI approaches helps one to predict and optimize the targeted properties of the Ti alloys. 308 Ti alloys were modeled by Noori Banu & Devaki Rani (2018) using ANN to design products with optimal mechanical properties and better bio-compatibility. The processing parameters and composition of the alloy were considered as inputs and mechanical properties viz yield strength, tensile strength and elastic modulus as outputs. The ANN model has predicted the influence of Tantalum and Niobium at high concentrations will increase the yield and tensile strength wherein it reduces the elastic modulus closer to the cortical bone. Sultana et al. (2014) developed a Ti alloy with high strength and low elastic modulus for use in prosthetics, where the needed qualities were inherently contradictory and require multi-objective optimization utilizing ANN and GA.

Four different optimization studies were done through multi-objective GA optimization using different developed ANN models with the objectives of maximizing three properties viz Yield Strength (YS), Fibroblast Outgrowth (FBG) and growth rate of L929 cells and minimizing the Young's modulus (E) of Ti alloy. The ANN prediction for the yield strength model has given a high coefficient of regression as 0.826 with the least error. Due to conflicts between different objectives, Pareto fronts with 3 different objectives in the combination of E-YS-FBG using GA have shown a maximizing trend in the required properties. The alloy composition of the corresponding Pareto solutions found to contain high amount of β stabilizers, as expected.

β-Ti alloy is one of the promising Ti-alloys for the use as bio-implants which can have low modulus and high strength. This can be achieved by synchronizing the content of β stabilizer. In the field of materials science, the neural network technique is widely regarded for detecting alloy properties such as thermal deformation behavior, formation of fatigue cracks, corrosive behavior, stresses, phase transition etc. (Sidhu et al., 2021). Quan et al. (2015) predicted the structural response in Ti-13Nb-13Zr alloy using ANN. C.-T. Wu et al. (2020) have presented an ANN based on machine learning to build a cheap Ti alloy with Young's modulus similar to bone. The final optimal network model for determining martensitic transition start temperature was 6–8–8–1, and a low-cost Ti alloy containing Ti-12Nb-12Zr-12Sn with a much low Young's modulus of 42.4 GPa was proposed. Yang et al., (2020) discovered that the cluster-formula integrated hybrid ML model offered a range of new low modulus Ti alloys, and that these estimated moduli were in excellent agreement with the experimental data. A similar ANN based design of β-Ti alloys was made by a number of other researchers (Sudhakar & Haque, 2013; Wu et al., 2022).

Datta et al. (2013, 2016) used multi-objective optimization studies to design β-Ti alloys for use in the application of a prosthesis utilizing Reduced Space Searching (RSS) Algorithm and Fuzzy inference system (FIS). The objectives of the study were to have high strength and a low Young's modulus along with defined biocompatibility of the β-Ti alloys. The three-layered FIS correlating the compositional and process variables with the microstructural parameters and finally with the properties were developed as shown in Figure 10. The rules were generated partially using the system knowledge and partially from the data.

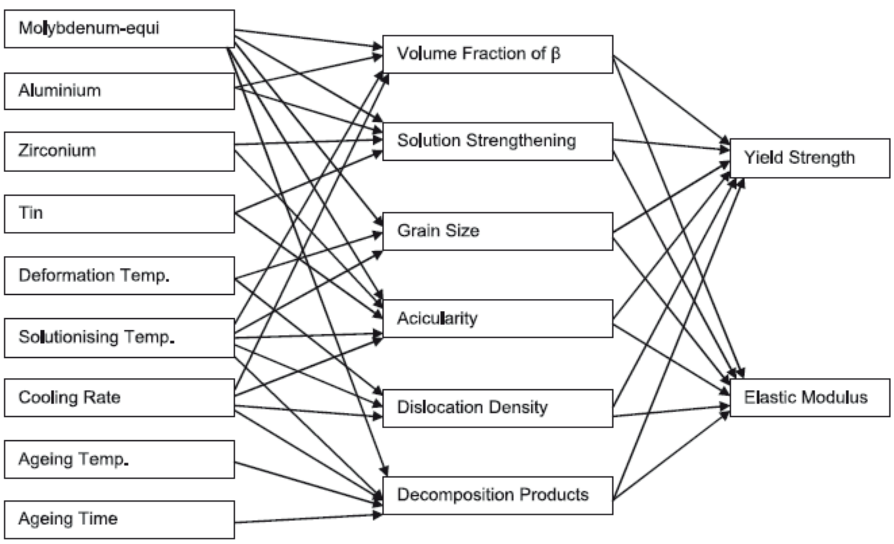

Fig. 10. Schematic diagram of the FIS correlating the properties with the composition, processing and microstructure (Datta et al., 2016)

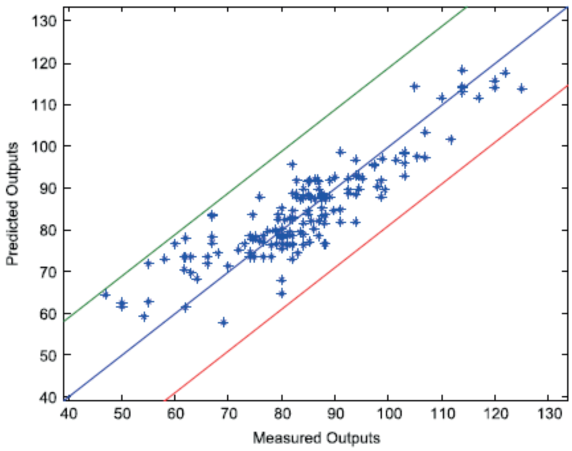

Fig. 11. Prediction of elastic modulus by the developed FIS (Datta et al., 2016)

Figure 11 shows the predictions made by the FIS. Here it can be noted that the predictions are quite acceptable considering the fact that the model has used the linguistic if-then rules also to describe the correlation. Figure 12 shows some of the simulation results in the form of surface plots generated from the predictions of the FIS. Here the correlation between the microstructural parameters and the properties was revealed quite effectively.

Figure 13 shows the Pareto front of the Young's modulus and yield strength. From the figure, it is evident that the there is a concise knee region in the front that shows the best area for the decision making as there was a shift from either direction of the knee region where the solutions lose one objective continuously with no significant gain in the other objective. Some sample alloy compositions that correlate to solutions in the knee region were taken as the Pareto solutions of the front, the Cr concentration was regularly maintained about 20 wt%, which ensures appropriate β phase morphology and thereby reduces the Young's modulus of alloys. Also, the need of aluminium (Al) and Tin (Sn) element is significant from the designed Ti alloys (Datta et al., 2013) which would pave a way of experimental development of the alloy.

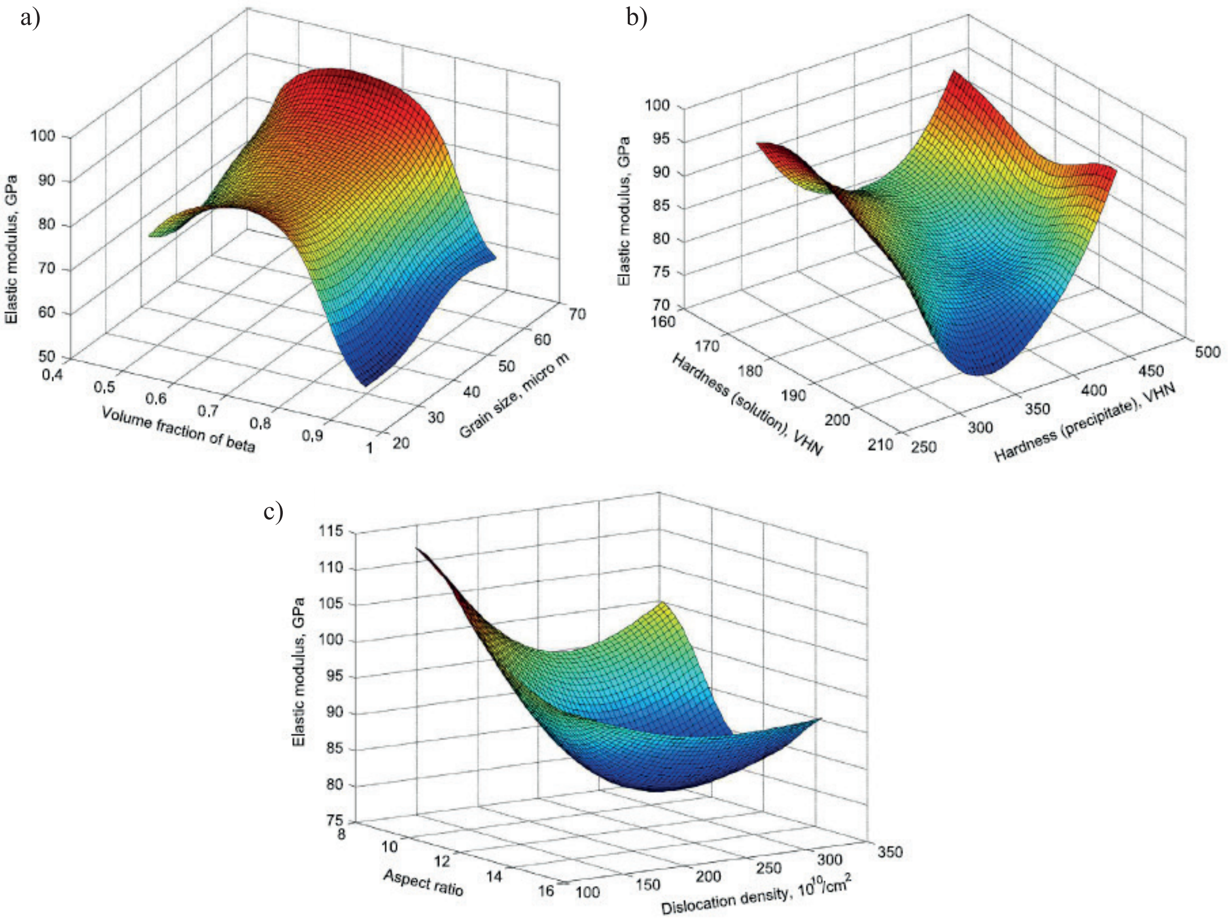

Fig. 12. Surface plots showing the relation between the properties and (Datta et al., 2016)

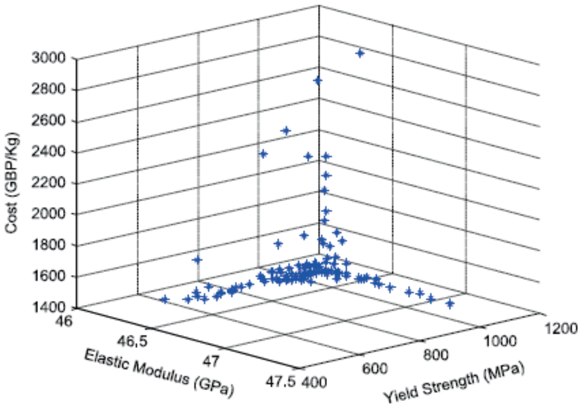

Fig. 13. Pareto front of E vs YS (Datta et al., 2016)

Another traditional methodology to predict the kinetic, thermodynamic and other related properties of multiphase materials models known as CALPHAD (Calculation of Phase Diagrams) was used by few of the researchers. (Chakraborti, 2022; Sundman et al., 2021). Jha & Dulikravich (2021) have identified the new compositions and temperatures of Ti-Nb-Zr-Sn alloy that will aid in increasing the β phase stability while reducing the ω and α phase formations for biomedical applications. This study helped to develop a newer Ti alloy using CALPHAD for analyzing the different phase's stability, Deep learning ANN models to predict the different phases of temperatures and new compositions. Further, they used self-organizing maps for finding the correlations among the composition, phase stability and processing temperatures.

3.2. Composites as biomaterials

The design of bio-composites using CI methods for a wide variety of medical applications have given some promising findings for medical practitioners in the decision making for several issues. The mechanical, wear and biocompatibility of the composites are optimized. The different classifications of bio-composites are broadly as Metal Matrix Composites (MMC), Polymer Matrix Composites (PMC) and Ceramic Matrix Composites (CMC). The applications of CI techniques for designing such composites are as follows.

Partially Stabilized Zirconia (PSZ) / Stainless Steel (SS) 316L bio-ceramic composites were designed and developed using two types of CI tools namely ANFIS and Support Vector Regression (SVR). These models were developed to predict the hardness and relative density values of PSZ/SS316L composites (Jajarmi et al., 2019). Both the model's accuracy was verified using statistical data viz determination coefficient, Root Mean Squared Error (RMSE) and Mean Relative Error (MRE). Both the developed models supplied better performance of the composites in comparison with the experimental findings. The predicted values given by the ANFIS model have low RMSE and a low percentage of MRE. The wear behavior of the SS/HAP bio-composites was analyzed using ANN by Younesi et al. (2010). The objective of the study was to predict the volumetric wear loss of the SS/HAP composites for the various wear distances and loads as the influencing parameters. The predicted results of wear loss by the developed ANN model were well matched with experimental results. Hence this model was used to find the wear loss of various composites at different values of wear distance ranging from 0 to 1000 m and various loads.

Thomas et al. (2020) designed a two layered Ti alloy / HAP composite for use as a dental implant with Ti alloy as inner core and HAP as outer shell using GA based multi-objective optimization. The inner core was meant to maintain the low stiffness of the structure, and in the outer shell HAP was added to make the implant bioactive for achieving superior osseointegration. The trained ANN models were utilized to predict the alloy properties. The ANN models were clubbed with rule of mixture for predicting the properties of the outer shell as well as the properties of the implant, and thus to form the objective function for achieving the high strength and low modulus of the implant. The optimization results showed that the β stabilizers like Mo, Sn and Cr were the preferred alloying elements. As the presence of β phase in Ti alloy decreases its modulus, the results are expected for lowering the stiffness of the implant. The optimum solution also had some amount of Al and Fe for maintaining the strength level. The HAP volume fraction varied between 5% and 6%. In the Pareto front, it was seen that for lower values of modulus the radius of the core was high and higher amounts of alloying elements to achieve higher β content.

Al-Waily et al. (2020) have analyzed the fatigue properties of removed denture that exposed to varying loads over time leading to failure under dynamic behavior. Two biomaterials namely HAP and Graphene Nanoplatelets (GNP) were chosen as reinforcements for analyzing the dynamic behavior of the denture. The ANN technique was used to predict the fatigue strength of the denture with the input parameters as the composition of reinforcements ranges from 0.25% to 1.25% of weight fraction. The ANN model has predicted a better influence on the addition of

2 reinforcements in a low amount to the denture that increases the fatigue life of it. From the findings of ANN, fatigue characteristics of GNP reinforced denture have given a better improvement in comparison with the HAP reinforced denture.

Hyaluronic Acid (HA) – Polyethylene Glycol (PEG) composites have been developed by Jeong et al. (2014) using ANN for the utilization in the applications of regenerating soft tissues and cell delivery. The aim of this study was to quickly monitor the formations of hydrogel in the HA-PEG composites. ANN model was helpful to correlate the relations among the parameters related to the hydrogel formation of HA-PEG composites and the measure of biological response of every type of cell in the intervertebral disc. The finding through the prediction of ANN was that the lower molecular weight HA yielded a higher amount of cell formation leading to multiple clusters of cells. R. Kumar et al. (2022) have made use of Taguchi and GA based optimization methods to predict the optimum dimensions of part in the manufacturing of polymeric bio-composites using Fused Deposition Modeling (FDM). The objective of the study was to minimize the variable dimensions of FDM based polymeric bio-composites. Through this optimization study, the influencing parameters that yield the accuracy in the dimensions of FDM parts were the orientation angle and thickness of the layer. The mechanical characteristics of epoxy nanocomposites reinforced with Graphene Oxide (GO) and HAP was enhanced using GA with the developed statistical models from ANN, RSM and decision tree approaches. Through modelling decision tree and ANN have given the better prediction of mechanical properties of epoxy/HAP/GO nanocomposites. GA was used to optimize the mechanical properties viz flexural strength, compression strength and flexural modulus. Both from modelling and GA based optimization, the lesser amount of GO and higher amount of HAP was required to improve the flexural and compression behavior of the hybrid epoxy nanocomposites.

Choudhury et al. (2022) designed and developed hybrid Polyether-Ether-Ketone (PEEK) composites for the application of cervical gages using ANN and GA by simulating the data through Finite Element Analysis (FEA). The FEA stress analysis was done on the cages of varying dimensions and shapes kept between C3 and C4 vertebrae level of the cervical spine. An ANN metamodel was developed from the simulated data for the stress analysis. The elastic modulus of the peek composites was also predicted by another ANN model with the correlation of various reinforcement particles. This model was acted among inputs of the formerly developed ANN metamodel. These two ANN models were used as an objective function for the GA based optimization studies. Pareto solutions from GA have given an insight on selecting the desired cages for the use in cervical spine.

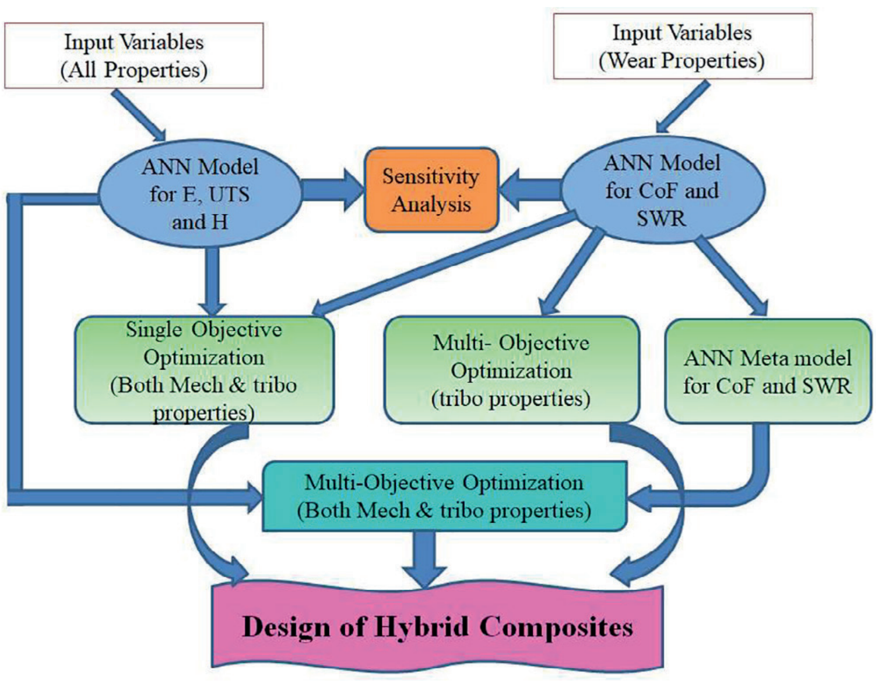

Fig. 14. The scheme of computation for designing UHMWPE composites (Vinoth et al., 2021a)

Computational intelligence based design of hybrid ultra-high molecular weight polyethylene (UHMWPE) bio-composites was developed for use in the acetabular cup of a hip prosthesis. The blend of ANN and GA approaches were used to predict and optimize the mechanical and wear properties of the UHMPWE Hybrid composites (Arulraj et al., 2022; Vinoth & Datta, 2020a, 2020b; Vinoth et al., 2021a, 2021b). The mechanical properties namely elastic modulus (E), Hardness (H) and Ultimate Tensile Strength (UTS) and wear properties namely Specific Wear Rate (SWR) and Coefficient of Friction (CoF) of the UHMWPE composites were considered as targeted parameters. The scheme of designing the composites is given in Figure 14. The geometry and weight percent of the four different nano/micro reinforcement particles were considered as the influencing input parameters. Individual ANN models were developed for each of the required properties of composites through iteration. The selection of the models was based not only on the higher regression coefficient, but also on the sensitivity analyses that exposes the correlation among the input and targeted output variables. The developed ANN models were then utilized as the objective function for the optimization studies using GA.

The objective was to maximize the mechanical properties and minimize the wear properties with necessary constraints to find the optimal percentage of composition required to manufacture the composites. Figure 15 shows the Pareto front for COF and the specific wear rate of the UHMWPE composites for varying molecular weight of the matrix material. Figure 16 shows the Pareto front when three objectives were considered together, i.e. two wear properties and one mechanical property. The optimum values design variables in the Pareto solutions provided a guideline for experimental validation.

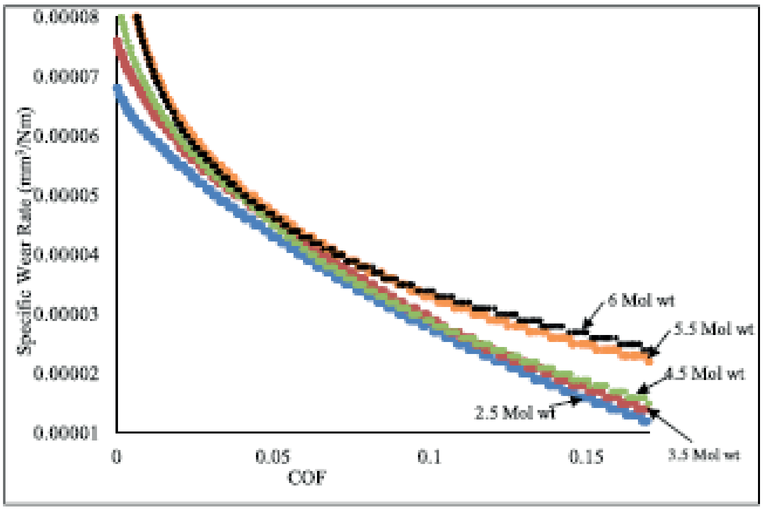

Fig. 15. Pareto front for COF and specific wear rate of the UHMWPE composites for different molecular weight of the matrix material (Vinoth et al., 2021a)

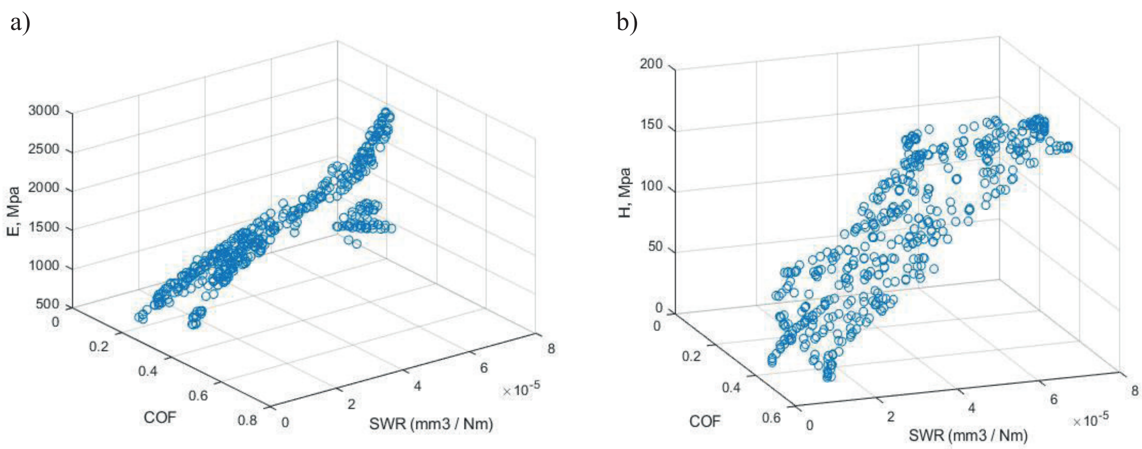

Fig. 16. Pareto front for optimizing three objectives: a) COF, SWR and E; b) COF, SWR and H for UHMWPE composites (Vinoth et al., 2021a)

The replacement of oil based biomaterials with starch based biopolymer composites led the way for many researchers to enhance the mechanical characteristics of such biopolymer composites. Guessasma & Bassir (2010) attempted to enhance the mechanical characteristics of Starch–Zein biopolymer composites especially on the elastic behavior of the composites. They used a numerical approach to studying the phase behavior (interfacial) and various elements of microstructures which were directly related to the elasticity of the biopolymer composites. A hybrid method relating the finite element method and a genetic algorithm was utilized that provided a relationship among the essential, interfacial properties and active properties of the composites. With the help of finite element outcomes, the determination of a suitable law for defining the active modulus of elasticity was established using ANN and GA methods. ANN predicted an open relationship among the elastic modulus and the microstructural behaviour of the composites. Through GA, it was found that the elastic modulus was linearly varied with the interfacial properties and has nonlinear behavior in terms of phase content.

Karimi et al. (2015) have investigated the effectiveness of the ANN approach for predicting the diameter of a nanofiber in order to determine the shape and thickness of the fiber. A blend of chitosan and poly vinyl alcohol (PVA) in varying proportions was used as a matrix nanofiber material. A dataset comprises of different samples of nanofibers was used for training and testing in the modelling of different ANN networks. A best model with 3 hidden layers iterated with 5, 8 and 16 hidden nodes was chosen. This model predicted a suitable fiber diameter with a better coefficient of correlation and least mean square error and proved the effectiveness of ANN during the prediction. To examine the implications further, a 3D plot involving the parameters of the electrospinning process and the diameter of nanofiber was designed.

3.3. Surface treatment of biomaterials and implants

The coating of biomaterials and surface modification are avenues which improve the surface characteristics of biomaterials. To understand the effect of the processing parameters with the surface characteristics, the use of CI approaches has paved a way for the researchers to design the biomaterials through surface modifications. Surface characterization of bone implant made of Titania (TiO_2) nanotubes was analyzed using fuzzy inference system. The fuzzy approach was used to determine the relative significance of various features of TiO_2 nanotubes on the surface of the bone implant based on its functions and the associated inter dependence properties (Martinez-Marquez et al., 2020). This requires an in-depth analysis for the optimization of the modified TiO_2 nanotube implants. The fuzzy inference system has given a relative influence of surface parameters like inter distance of nanotube and diameter of pore which facilitate the biological and mechanical behavior of the implants.

AI based modelling of a HAP coated cobalt chromium alloy (CoCrMo) for the enhancement of corrosion behavior for use in biomedical applications has been attempted by Coşkun & Karahan (2018). They have developed two distinct models using ANN and Genetic Programming (GP). The same has been compared with the RSM model. Parameters related to the electrodeposition of HAP on the CoCrMo bio-implant were considered as inputs and the E_{corr} values and corrosion potential were considered as outputs for the AI models. Each distinct ANN and GP models were developed for each output with three input variables. In comparison among all the three methods, ANN models have given a considerable prediction of influencing parameters on the required corrosion properties.

Nighojkar et al. (2022) have studied the importance of metal adsorption through biomaterials in water contaminant systems. To improve the adsorption behavior of the biomaterials, surface modifications and physical changes were required. In the effort to comprehend the intricate metal adsorption characteristics of biomaterials, ANN has been used to achieve better environmental restoration and reuse of waste water. They have reviewed the use of hybrid ANN to determine the thermodynamic, kinetic and isothermal properties of multiple adsorption systems. The dataset was generated with the experimental data of various biomaterials related to the contact time, concentration of metals in the biomaterial and its time of equilibrium. ANN models were developed to predict the influencing kinetic characteristics and the uptake capability. The same way ANN models were developed for the adsorption isotherm and thermodynamics properties (range of temperature and adsorption nature). RSM was employed to understand the causes of interaction among the adsorption parameters (Kartal & Özveren, 2021) in comparison with the ANN models. An ANN based GUI for researchers who were not much familiar with the computational approach of attaining data related to adsorption was proposed by Narayana et al. (2021). Due to convergence of ANN into the local minima, metaheuristic approaches were framed for effective optimization. Hamidian et al. (2019) have developed a search algorithm in combination with ANN for the optimal removal of heavy metals through nanomaterials based on chitosan.

Likewise, the prediction of self-assembled nano-biomaterials for effective use in biomedical applications is another regime of utilizing CI approaches. Kwaria et al. (2020) have attempted to predict the protein adsorption and contact angle of water on the self-assembled mono layered biomaterial using ANN models. ANN has given a better correlation to reveal the surface characteristics of the biomaterial with the effective adsorption rate of protein and water contact angle. The statistical (multiple linear regression) and ML (ANN) approaches were employed to study the phase behavioral changes of nanomaterials that have lipid base, monoolein and various composition of fatty acids in saturated and unsaturated forms (Le & Tran, 2019). The ANN models have an appropriate prediction of phase behavior under various phases with greater accuracy of the model ranges 66% up to 96% in comparison with the linear regression model. This has paved a way for utilizing these models for suitable lipid-based delivery systems.

The corrosion rate of magnesium in a degradable biomaterial can be controlled for potential use in biomedical applications (Willumeit et al., 2013). The experimental dataset related to the CO_2 corrosion rate and the NaCl concentration was considered for the development of the ANN model. The ANN has revealed the increase in the CO_2 corrosion rate with its increasing concentration that too specifically ranges from 0% to 5%. In this way, ANN helped to identify the influencing parameters that deteriorate the corrosion rate that typically indicates the assessment of novel biodegradable materials under in-vitro conditions. The optimal conditions for the biofilm removal on the surface of the antibiofilm activity of α-Amylase biomaterial was predicted using ANN and RSM methods through the study done by Lahiri et al. (2021). ANN and RSM techniques have predicted the optimal conditions involving the concentration of enzyme, time of surface treatment and pH level of the medium for the higher eradication of biofilm. This computational approach helped the medical community for the potential removal of the biofilms that creates various severe infections near the surrounding tissues of the implanted biomaterials.

The mechanical and biological behavior of the surface polyvinyl pyrrolidone coated bio-ceramic nano magnetite / zirconia particles in a porous biomaterial used as a scaffold was predicted utilizing the fuzzy techniques (Li et al., 2022). The fuzzy logic models were developed to predict the fracture strength, strain rate, compressive strength of the porous calcium carbonate scaffolds coated with the magnetite and zirconia particles. Also it has helped to predict the biological parameters like the formation of apatite and biodegradation rate of the porous biomaterial. The optimum surface topographies of biomaterials were evaluated through an evolutionary algorithm (EA) in the study done by Vasilevich et al. (2020). To investigate the interactions between implanted device coatings with tissues and cells, they employed quality of clinical screening of vast banks of materials with varying surface topographies. However, due to the huge breadth of the variable design space, a brute strength method cannot be used to filter all topographical alternatives. Using evolutionary algorithms, they optimized surface topographies inspired by nature. They demonstrated that consecutive stages of material design, manufacture, fitness evaluation, mutation and selection optimize the design of biomaterials. They employed randomized mutagenesis and crossover to build new generations of topographies, beginning with a small number of topographically engineered interfaces that regulate the development of an osteogenic indicator.

The coating of biomaterials on the titanium alloys and surface modification are the avenues which improvise the surface characteristics of Ti alloys. Spin coating of biopolymers onto a commercially pure titanium was done followed by electrochemical impedance spectroscopic characterization. ANN was utilized to estimate the values of open circuit potential (OCP) in an uncoated and coated cp Ti alloy that enhances the corrosion resistance of the biopolymer coated cp Ti alloy (Kumari et al., 2018). Likewise, Kazemi et al. (2022) investigated the corrosion resistance of a Ti alloy (Ti-6Al-4V) by coating hydroxyapatite (HAP) using the ANN approach. The parameters were related to the sol-gel preparation of HAP that was considered to be inputs and the output was the measured experimental Ecorr data. The trained ANN model has given a better prediction on the Ecorr values providing good corrosion resistance of Ti-6Al-4V alloy in comparison with the developed RSM and gene expression programming models. A non-dominated sorting genetic algorithm II (NSGA II) was utilized for the optimization of micro hardness and roughness of β-Ti alloy surface (Prakash et al., 2016). The objective of the study was to reduce the surface roughness and increase the micro hardness of the surface with optimal surface machining parameters. The same has been achieved by generating models using the RSM approach and optimizing the process parameters using NSGA II. A similar study on improving the surface roughness of another Ti alloy (Ti-13Zr-13Nb) with sulfuric acid etching was done by Khanlou et al. (2016) using blended neuro-fuzzy inference system (ANFIS). The time of etching and temperature were the influencing input parameters that improve the surface roughness of the Ti-13Zr-13Nb alloy.

ANFIS model has predicted a better correlation among the input parameters and surface roughness to achieve a good mathematical model with a Gaussian membership function.

3.4. Materials for drug delivery systems

The use of CI techniques for the development of new biomaterials in the field of drug delivery is helping the medical community in numerous ways. The ANN approach was used to design and model a bio-nanocomposite in order to optimize the hydrogel wound dressings. Water Vapor Transmission Rate (WVTR) and the correct Degree of Swelling Ratio (DSR) were the properties enhanced to overcome common concerns with commercial wound dressings, such as inadequate breathability and fluid absorption. The bio-nanocomposite developed by Joorabloo et al. (2019) have also shown enhancement in the mechanical properties and bio-compatibility which would help in the better healing of wounds and protection capabilities.

The ANN approach has been utilized for the formulation of a self-nanoemulsifying system for drug delivery based on optimizing their physicochemical properties (Vu et al., 2020). The neuro-fuzzy model was employed to predict and correlate the In vitro–in vivo self-emulsifying systems for drug delivery for lipid based preparations (Fatouros et al., 2008). In order to predict the formulation impact and various process parameters involving the release of prednisone through a multi-unit pellet method, multiple layer perceptron trained – back propagated ANN model was used (Manda et al., 2019). The prediction revealed that the prednisone release was predominantly due to the concentration of crystalline cellulose in a micro scale. The ANN based drug delivery system has also used to predict the dissolution of drug (Benkő et al., 2022). Muñiz Castro et al. (2021) have reviewed the use of machine learning models that were helped to predict the role of process parameters for the manufacturing of 3D printed medicines utilized for drug delivery. The process parameters for the extrusion of filament have given a prediction accuracy of 93%. ANN model has yielded the best prediction towards the drug release times. Likewise, a 3D printed drug distribution scaffold in the area of tissue engineering was developed using ANN. The ANN predicted model has given an enhancement in chemical, mechanical, repair and bone healing properties of a 3D printed bone scaffold for the drug release controller (Kondiah et al., 2020). Similarly, a novel tablet for oral disintegration was developed for pediatric patients using an ANN predictive model which can dissolve at a faster rate. This predictive ANN model has reduced the timeline on developing the drug in a robust manner with minimal material usage (Han et al., 2018).

The Fuzzy Logic (FL) approach utilized by Kumar & Raj (2022) helped to model and design a controller for the automatic delivery of drug for monitoring and regulating arterial blood pressure. This FL model has controlled the drug infusion rate of sodium nitroprusside in a rational limit and the same has been validated with the experimental results. This FL based controller has also shown an improvement in the overshoot and settling time of the drug. The lack of a micro pump renders the drug delivery method insufficient. The Fuzzy controlled micro pump was presented to determine the velocity and flow rate of the drug. The simulation was based on real-time fluidic parameter situations. The difference between the modeled and measured values of flow rates was only 1 microliter per minute and a drug speed of 0.01 milliliter per second (Farah & El-Sheik, 2021). A similar FL based approach for drug delivery was investigated by Nazari et al. (2021) for cancer patients during the process of immuno- and chemotherapy according to the ages of the patients. The proposed FL based algorithm has given oncologists the ability to prescribe treatment protocols of cancer patients in an optimal manner based on their ages. By creating two ideal nonlinear controllers, the adverse reactions of pharmacological therapy for cancer medication can be minimized. The associated benefits of the developed controllers were simultaneously optimized with the GA based evolutionary algorithm and modified with the fuzzy scheduling approach (Ghasemabad et al., 2022). The medication seeks to lower the number of cancer cells by delivering a dosing regimen of drugs using the developed GA controller.

Microrobots were used for drug delivery in a controlled manner on planning the path coverage area (Tao & Zhang, 2005). GA based approach was utilized for the enhancement in the effective path utilization of microrobots when compared to the conventional path planning techniques. GA based approach has reduced the computational time and costs and also improved the optimality of the path for the drug delivery. ANN-metaheuristic based design and optimization of synthesis of nanovectors for various applications in the drug delivery equipment was investigated by Villaseñor-Cavazos et al. (2022). ANN and FIS model have given a best prediction towards the properties of drug delivery systems like particle loading and size. The metaheuristic-based optimization studies have shown optimal nanovector's properties. Multi-objective based GA approach was used to model and control the particle size in a closed loop for the release of Poly Lactic-co-Glycolic Acid (PLGA) nanoparticles into the drug delivery system (Baghaei et al., 2017). The optimal minimal particle size was achieved through the GA study and the uniform distribution of the particles and its size was also validated through the experimental characterization. Similar work was done by Rafienia et al. (2010) on the controlled drug delivery of PLGA using ANN. The comparison of three types of feed forward neural networks to determine the nonlinear relationship among the formulation of drug loading and the release profiles. Out of different ANN, the Multilayer Perceptron (MLP) model was more consistent and efficient on finding the drug release profiles. As a unique class of carbonaceous nanomaterials, graphene has gained considerable interest in the domain of drug delivery. GA based optimization was done to search for the global optima binding interaction of graphene and the drug to be delivered in the graphene-based drug delivery system. Here the fusion of quantum mechanics and GA based CI platform named e-graphene (Zheng et al., 2021) was developed to predict the feasible parameters of graphene based drug delivery system.

3.5. Materials for scaffolds

The importance of the fabrication of 3D objects in the field of bone tissue engineering (BTE) is growing. The computational intelligence methods of developing scaffolds for the growth of tissues are predominant. Affecting factors for BTE scaffolds are mechanical characteristics and porosity. Operating parameters have a significant impact on the mechanical characteristics of scaffolds. Layer thickness, delayed time in dispersing every layer of powder, and printing orientations are the key determinants of the 3D printed scaffold's porosity and compression strength. The influence of all the processing parameters on the porosity and compressive strength was analyzed using aggregated ANN (Asadi-Eydivand et al., 2016). Also, Particle swarm and Pareto front optimization methods were utilized to find the best Aggregated ANN topology and setting parameters for the manufacture of scaffolds with the necessary porosity and compressive strength. Similarly GA based optimum compressive strength of the scaffold was achieved by Abbas et al. (n.d.) and Al-dujaili et al. (2017) in their studies.

Electrospun scaffolds made out of suitable polymers require high mechanical properties especially of the elastic modulus of the micro and nanofibers of electrospun scaffolds (Vatankhah et al., 2014). The geometry of the fiber and composition of the polymer are the important factors that affect the elastic modulus. The ANN model helps to determine the influencing factors to attain an enhanced elastic modulus of the scaffold. This will in turn helps to enhance the required mechanical properties of the targeted tissue. ANN was used by Reddy et al. (2021) for finding the correlation among the electrospun processing parameters and tensile strength of the electrospun polycaprolactone scaffolds along with their suture retention capabilities. Similarly, ANN aims at determining the influence of electrospun parameters in the alignment of poly glycolic acid and polycaprolactone blended nanofibers (Paskiabi et al., 2015). GA based optimum model has shown an enhancement in the elastic modulus of the scaffold made by a biomaterial Alginate for the soft tissue applications (Rezende et al., 2009). This GA model would guarantee the appropriate stiffness and strength of the scaffold. The design of a composite nanofiber was achieved by GA utilizing the models developed by a trained ANN and response surface methodology (RSM) (Haghdoost et al., 2022). The ANN model has given a high goodness value from a novel goodness function compared with the RSM Model. A similar study was done by Shera et al. (2018) using ANN and RSM models to develop a scaffold with natural composite that releases the drug in a diffusion controlled environment. This developed model was used to predict, regulate and screen the cell response on growing tissues.

Cell culture properties and the architecture of the scaffold was optimized using a genetic algorithm (Domínguez-Díaz & Cruz-Chavez, 2015). This GA based model aims at improving the growing of osteoblasts on polymer scaffolds by controlling their processing parameters and architecture. The results were compared experimentally and consistent improvement was observed. Semnani (2014) has proposed a GA based optimum model for the distribution of nanofiber in the structure of the scaffold. The experimental outcomes have given a tremendous improvement in the tensile and surface properties of the results. Likewise, another crucial factor influencing the tissue regeneration issue is the stiffness of the scaffold. Nanofiber scaffolds made of cellulose acetate and gelatin was optimized the responses using RSM and ANN. The optimal parameters for manufacturing better nanofibers with a minimal diameter and suitable composition of gelatin and acetic acid were found by Khalili et al. (2016). Heljak et al. (2017) have developed a GA model to design an optimum scaffold architecture for controlling the hydrolytic degradation with the targeted elastic modulus of the scaffold material.

The objective of another work (Heljak et al., 2012) was to develop a numerical tool using GA that could aid in achieving the intended behavior of tissue-engineered scaffolds, and the findings shown were accomplished effectively by utilizing a wide range of materials for particular scaffold. Meta model optimization utilizing

GA with the data generated from the finite element analysis model for finding a suitable stiffness of the scaffold was proposed by Paz & Monzón (2019). This blended optimum model has given a feasible stiffness of the scaffold to control the function of the cells. The detection of porous characteristics of microstructural images of scaffolds was analyzed using GA. The analysis of images by the GA model has given an agreeable comparison with the experimental data related to the distributions of pores, elongation and orientation of pores (Rouhollahi et al., 2021).

In order to treat vascular diseases, implantation of the bio-absorbable artificial stent is much preferable. To spot the stents in the blood vessels effectively, various bioresorbable scaffolds from medical images were utilized. A convolutional neural network (CNN) in 'U' form (Zhou et al., 2019) was developed to predict the identical samples of tomography images of bioresorbable scaffolds. This has paved a way for the doctors to diagnose diseases and finalize their decisions. To monitor the inhibitors of MMP2 enzyme depending on L tyrosine scaffold, a blend of GA and partial least squares model was developed to along with the multiple linear regression model (Abbasi et al., 2015). These developed models predicted the need of flexibility, molecular size, shape, and branching degree of various atoms in a molecule against the MMP2 enzyme in the scaffold.

3.6. Design of biomedical implants

Although designing a biomedical implant or prosthesis is not same as designing biomaterials, materials play an important role in the design of all implants. Without considering the materials properties or the limitations of materials to be used, it is not possible to design the implants. Newer materials with improved properties compel the biomedical engineers to modify the old design. In such a situation, it was decided to include a section for designing implants in this review. The design of artificial implants using CI methods has given a wider dimension in the field of orthopedics. Various implants include joint prosthesis, dental implants, spinal implants etc. CI Methods were utilized to determine the implant material characteristics to improve the structural and physical behavior. Zaw et al. (2009) have proposed the inverse approach of analyzing the elastic modulus of the contact tissue among the associated bones and the dental implant. They used a blend of neural network and reduced basis method (RBM) models under harmonic loading conditions on a dental implant for analyzing the displacement of the implant and the structure of the bone. The RBM model was utilized to train the neural network model for inverse analysis of elastic modulus. Experimental displacement values were given as inputs to the trained neural network model to inversely find the true modulus of elasticity of the contact tissue. This RBM / neural network model has given better and more reliable results compared to predicted and experimental values.

An ANN approach using a feed forward network was used to design the gait patterns to minimize the contact loads in the knee prosthesis. The dataset related to various experimental gait data were collected from the literatures. The study was to find the suitable waveforms of kinematics for corresponding patterns of loading that is required for a suitable knee joint. ANN has predicted a viable kinematics to reduce the contact reaction forces of knee joint (Ardestani et al., 2014). This CI based approach has given lot of insights for designing the knee joint prosthesis. ANN and GA were employed in a blended mode for an optimal design of femoral implant that has enhanced stability. Various design variables related to femoral stem were considered as inputs that would reduce the stability in the long term for the hip stem that purely rely on more relative motion (output) between the implant and bone (Chanda et al., 2015a). Several designs were made through finite element methods that would increase the computational time and effort rather than using the CI techniques for the optimal design. ANN using a backpropagated algorithm was used to predict the relative motion between the implant and bone and the predicted NN model was used as the objective function for GA in order to reduce the relative motion based on various conditions of loading in hip arthroplasty. The prediction on relative motion and optimal stem design through GA has given an enhanced stability in comparison with the finite element analysis. A similar method was used by the same authors (Chanda et al., 2015b) for the shape optimization of a femoral implant in the multi-objective optimization using ANN and GA.

Dental implants using functionally graded material (FGM) have given newer dimensions to overcome the mechanical properties mismatch among the tailored and actual biomaterials. Sadollah & Bahreininejad (2011) has proposed a way to design an optimal FGM dental implant utilizing the metaheuristic algorithms like simulated annealing (SA) and GA. This GA/SA approach of designing the FGM dental implants have given enhanced mechanical properties that would guarantee the matching of the required properties with the actual bone. The GA/SA based optimal results were very well comparable with the literatures. Ultrasonic response of osseointegration phenomenon in the interface of bone implant was analyzed using convolutional NN (CNN).

The objective of the study done by Kwak et al. (2021) was to develop an approach to evaluate the thickness of the soft tissue at the interface of the bone implant related to the ultrasonic response analysis. The prediction given by the trained CNN has given a better correlation among the targeted and actual thickness of the soft tissue. This has shown a convincing outcome on the roughness value in a micro and macro scale that supports the dependability of the predicted evaluation of the osseointegration phenomenon.

The successful use of dental implants was evaluated using a combined hybrid model of predictive analysis classifiers (Moayeri et al., 2016) such as NN, K-NN, Weka J48, support vector machine (SVM) and naïve Bayes. The effectiveness of the suggested technique was compared to that of individual classifiers. According to the findings of the investigation, the combinative methodology can obtain better output than the greatest single classifier. When the combinative method was used, the sensitivity indicator was enhanced up to 13.3%. In order to select different bio-materials for the use in an orthopedic implant named bone staple, Fuzzy logic and Gray Relational Analysis (GRA) models were used by Sanghvi et al. (2021). The parameters that decide the material selections were mechanical properties, the feasibility of manufacturing and biocompatibility and the materials in the dataset were Nitinol, Ti_6Al_4V and SS316L. This CI method of material selection helped considerably in determining which material can be used for the application of bone staple.

To assess the changes around the hip implant after the surgery, a neural network was used. NN has predicted the variations around the hip implant that shows the plan for the surgery and to find the risky regions where the decalcification of bone and the stability loss can be possible near the contact between the bone and implant (Szarek et al., 2012). Similarly the detecting the loosening of the hip implant through the radiographs was predicted using CNN (Borjali et al., 2019). The deepest CNN has given a better prediction than the other types of CNNs that will show the clinicians to make a decision on the diagnostics of mechanical loosening of the hip implant. The same authors (Borjali et al., 2020) utilized deep CNN to detect the design of a damaged hip implant preoperatively in a matter of seconds, reducing time and enhancing detection performance. Likewise, five types of deep CNN have been used to classify dental implant systems (Sukegawa et al., 2020) accurately through the dataset containing the various x-ray images of 11 implants. Kim et al. (2020) have used deep CNN to classify the implant fixtures through images of four different types of implants. Five CNN models were developed and all showed a better accuracy of the implant fixtures. Deep CNN was examined by Cha et al. (2021) to detect the implants' bone density level, apex, and top through dental periodontal radiographs. The proposed automatic assistance system was for assessing the percentage of bone loss and the severity of bone resorption. Similarly, deep CNN was used to classify the dental implant systems through radiographic and panoramic images (Lee & Jeong, 2020).

GA was used to optimize the location and geometry of the implant for the transfer of tendon surgery in the hand (You et al., 2021). The torque of the joints and kinematics of the fingers were utilized to develop three different objective functions for finding the optimal parameters of the implant. GA based design of implants provided the 11 fold enhancement of the finger kinematics with the reduction of 0.9% of the joint torque in comparison with the biomechanical function. Likewise, a blend of ANN/GA methods helped to design a spinal implant for the fixation of pedical screw (Biswas et al., 2018). A FEA simulated dataset consists of conditions of bone and implant diameter for varying loads and materials was used to develop ANN metamodels for the optimization of maximum composite desirability using the minimal microstrain difference under six different positions. Six ANN models for the different positions were able to show good predictions. The composite desirability function (*D*) values of the developed ANN models have been used for GA. The maximum attainable value for the *D* was 1. This was only possible if each individual's desirability was equal to one, hence the "strain difference" values for all six situations must equal zero. This scenario couldn't be concurrently obtained in all six bone conditions and locations. Optimization studies were reported using two different methods; firstly, for three conditions of bone i.e. 2.2 GPa, 2.5 GPa, and 3 GPa, five different body weights were evaluated to determine the maximum D value with minimal differences in strain for six positions and optimal diameter of implant. Secondly for three different weights of the body viz 420 N, 490 N, and 588 N, five conditions of bone were evaluated to determine the maximum *D* value and optimal diameter of implant. The results suggested that the goal of designing patient-specific spinal implants could be partially attained by altering merely the implant diameter. A similar method of blending ANN and GA was followed by Roy et al. (2018) to design patient-specific dental implants. The scheme of the research is given in Figure 17. Finite element analyses of the implant were done putting implants of varied diameter, length and porosity into the mandible of varied bone quality, as in Figure 18. The porosity was induced to reduce the stiffness for better osseointegration, as discussed earlier.

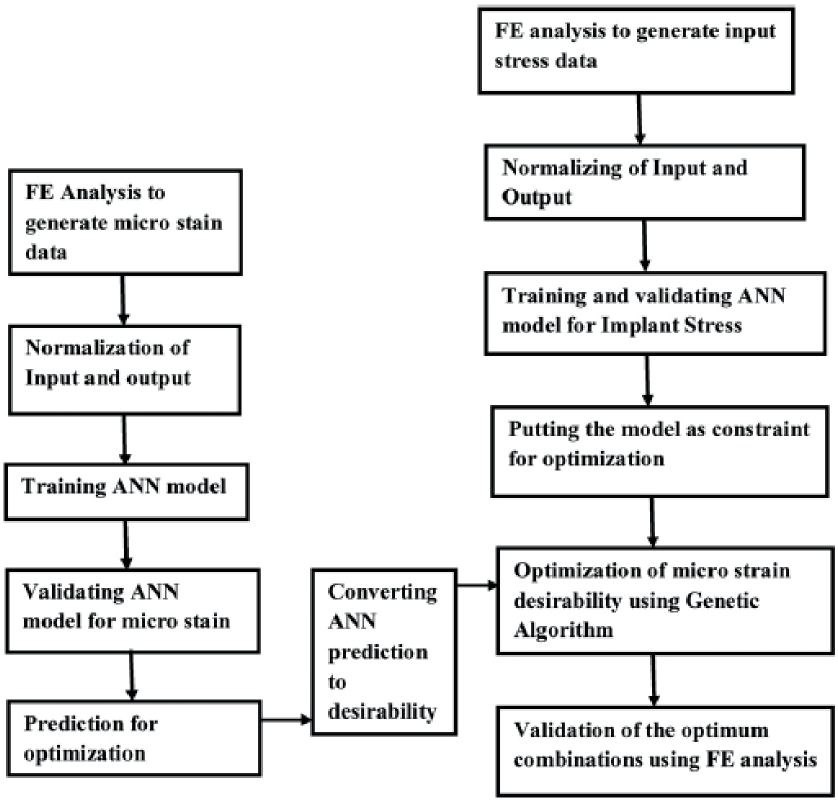

Fig. 17. The scheme of designing porous dental implant (Roy et al., 2018)

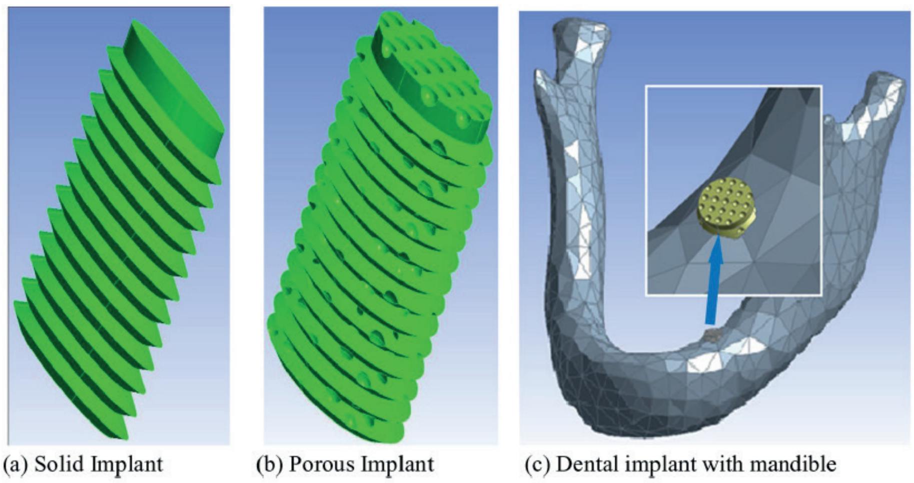

Fig. 18. 3D models used for the simulations using FEM (Roy et al., 2018)

The generated microstrain at the bone-implant interface and the maximum von Mises stress generated in the implant were recorded. ANN metamodels were developed to predict the microstrain as well as the stress at the implant. The targeted microstrain was 2500 with an acceptable variation between 1500 to 3000. Thus, the ANN metamodel outputs were combined to a desirability function, which converted the output to a value between 0 and 1, as explained in Figure 19. This combination of the ANN model with the desirability function acted as the objective function for the maximization of the desirability. The maximum stress was constrained with the ANN model for the stress was used as the constraint function. The optimum design variables developed for different bone conditions are plotted, as shown in Figure 20.

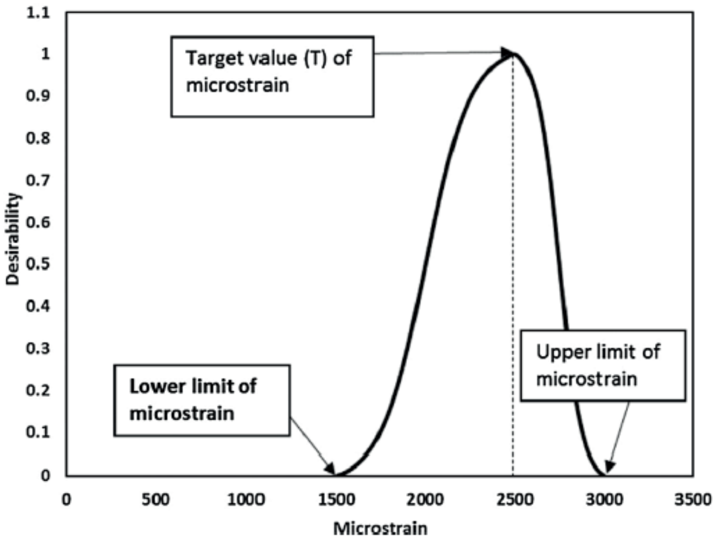

Fig. 19. Desirability function for the microstrain at the bone-implant interface (Roy et al., 2018)

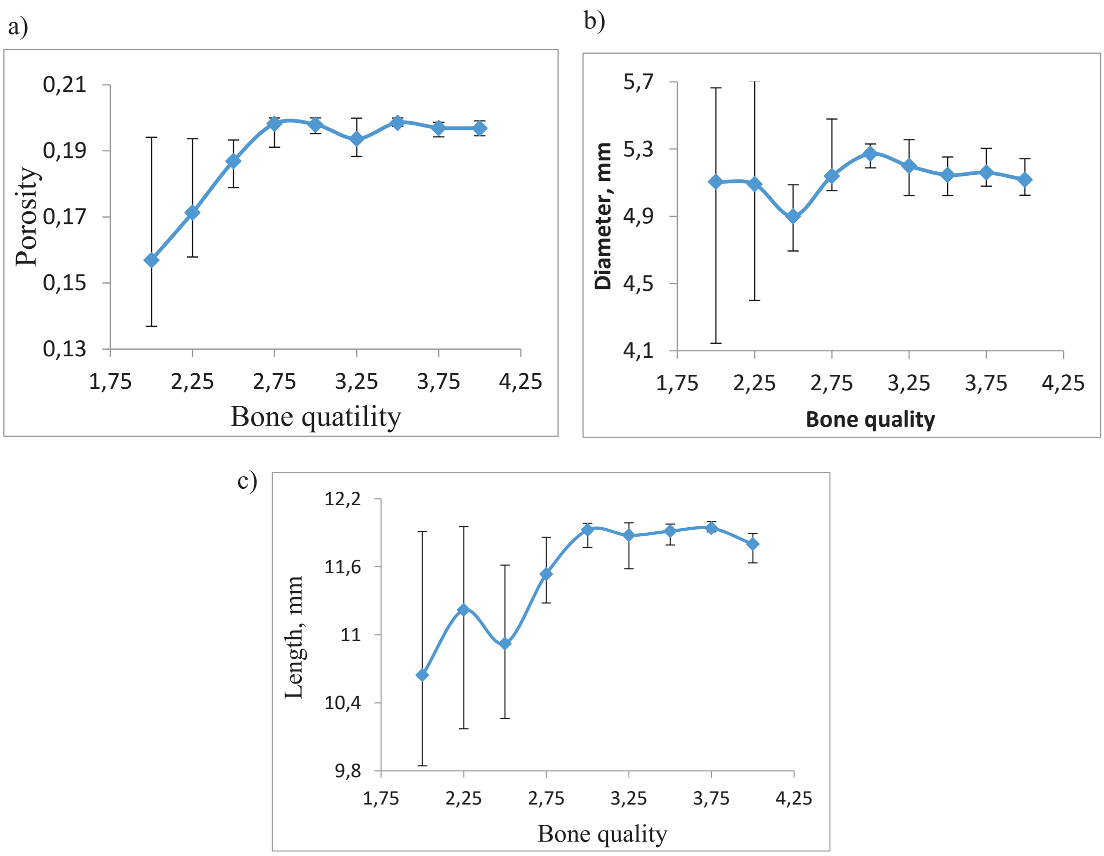

Fig. 20. Optimal values of: a) diameter; b) porosity; c) length of the dental implant for various conditions of bone (Roy et al., 2018)

The identification of damaged implant was performed by ANN for the preplanning in a revision surgery of total hip joint. The study done by Murphy et al. (2021) aimed at the construction of a ML algorithm employing active large data to recognize an implant from radiographic images; and to investigate algorithms that provide optimum accuracy in a quick manner. ANN models were developed to classify the radiographic images based on the implanted femoral stem. Through the earlier surgery reports, model and brand of the stem was confirmed. The performance of the ANN model was found by the accuracy of the classification. This ANN models offered better solutions for the surgeon to classify and identify the failed implants in a preoperative condition. Likewise NN techniques were used to categorize two kinds of hip implants according to the relative side speed of the implant and three elements of every ground reaction force during a normal walking gait (Parisi, 2014). The hip implants were categorized into three ways as Type I, II and III where Type I & II were based on the forces of ground reaction taken from different patients and Type III was based on the load on the bone. A multilayer perceptron NN was used to categorize the hip implants that have given a higher rate of accuracy in assessing the performance of the hip implants.

Knowledge based, rule based, and metaheuristic (GA) methods were employed to find the optimum design of patient specific implants used for ENT applications during its manufacturing (Chua & Chui, 2016). The manufacturing aspects of such implants considered were (*i*) its material properties and composition, and (*ii*) its geometry. The above-mentioned methods outperformed for determining the composition of the material in a multi-objective optimization fashion for the additive manufacturing of patient specific implants for the use in ENT applications. Similar knowledge imprecise CI methods using ANFIS and whale optimization algorithm (Sai et al., 2020) were chosen for the optimization of polylactic acid implants by printing it through fusion deposition method. Chatterjee et al. (2019) have used CI techniques (ANN/GA) to have the zero-strain difference adjacent to the femoral implant before and after implanting it. ANN meta-models generated through FEA simulation have been used as an objective function for the GA based optimization using the desirability functions of the ANN models. The optimum geometry of the implant for varying bone conditions were attained that act as a base to design a patient specific implant. Likewise FEM and computational approaches in tandem was deployed by few other researchers (Duan et al., 2018; Madi et al., 2013; Maeda et al., 2005) like finding the optimal orientation of fixation screws for the fractures of the femoral neck (Özkal et al., 2020) and design optimization of a single piece ceramic dental prosthesis (Cheng et al., 2019) subjected to dynamic loading using GA.

4. Concluding remarks

The review of the published literatures on the applications of ANN, FL and GA on the modeling and optimization of properties of biomaterials reveals that, like other domains of materials science and engineering, even though the tools have been used effectively by several researchers in a sizable number of published works, the full capacity of the work has still not been revealed. The reasons are manifold. Firstly, materials scientists have a higher inclination for experimental work, which has started changing. The efficacy of using computation tools before experiments through reduction of time and expenses is now getting revealed to wider number of scientists. The second reason might be an absence of sufficient data in the domain of biomaterials. As in this is comparatively smaller domain of research, where complicated experimentations are also needed frequently, the generation of a database good enough, where complex ML tools like ANN can be applied, becomes difficult. The third reason might be commercial. Volume-wise, the requirement of novel materials in the domain of biomedical engineering is quite low compared to others. In such a situation there are not enough encouragement from the industry side for developing newer and better materials. For example, while it is well-known that β-Ti alloys are better suited for hard tissue implant for their lower elastic modulus, but still the majority of such implants are developed using Ti-6Al-4V, as it is a widely used alloy and easily available in the market. The situation is definitely changing towards a brighter future with more and more researchers adopting CI tools in their quest for new materials. In case of biomaterials also such changes will be evident in the forthcoming days. But the requirements of tailored biomaterials are really high, as the properties of the materials used for prostheses or scaffolds required for any particular application is quite stringent. The requirements even vary with person to person. In such a situation designing a material with a strict combination of properties with a lower tolerance, applications of CI tools are more pertinent compared to materials used in other engineering applications. The constraints like biocompatibility have also to be dealt in such designs quite meticulously.

In many cases, efforts are being made to replace metal or ceramic prostheses by polymer or polymer composites-based implants. There are some expected advantages, such as better biocompatibility with lower density and price. In some cases, the implant is required to be anisotropic, which is difficult to achieve through metals or ceramics, but can be designed as per requirement using continuous fiber reinforced composites. For all such requirements, the informatics-based design of biomaterials with the judicious use of CI tools can provide effective solutions.

References

Abbas, H.N., Jaheel, S., & Al-dujaili, M.A.A. (n.d.). Optimize of the mechanical and physical properties of Ha/B-TCP scaffold by using genetic algorithm method. *The Iraqi Journal for Mechanical and Material Engineering*, Special issue, 266–281.

Abbasi, M., Ramezani, F., Elyasi, M., Sadeghi-Aliabadi, H., & Amanlou, M. (2015). A study on quantitative structure-activity relationship and molecular docking of metalloproteinase inhibitors based on L-tyrosine scaffold. *DARU Journal of Pharmaceutical Sciences*, *23*(1), 1–10. https://doi.org/10.1186/s40199-015-0111-z.

Al-dujaili, M.A.A., Jaheel, S., & Abbas, H.N. (2017). Preparation of HA/β-TCP scaffold and mechanical strength optimization using a genetic algorithm method. *Journal of the Australian Ceramic Society*, *53*(1), 41–48. https://doi.org/10.1007/s41779-016-0007-5.

Al-Waily, M., Al Saffar, I.Q., Hussein, S.G., & Al-Shammari, M.A. (2020). Life enhancement of partial removable denture made by biomaterials reinforced by graphene nanoplates and hydroxyapatite with the aid of artificial neural network. *Journal of Mechanical Engineering Research and Developments*, *43*(6), 269–285.

Anderson, J.A. (1995). *An Introduction to Neural Networks*. A Bradford Book, MIT Press.

Ardestani, M.M., Chen, Z., Wang, L., Lian, Q., Liu, Y., He, J., Li, D., & Jin, Z. (2014). A neural network approach for determining gait modifications to reduce the contact force in knee joint implant. *Medical Engineering and Physics*, *36*(10), 1253–1265. https://doi.org/10.1016/j.medengphy.2014.06.016.

Arulraj, V., Datta, S., & Davim, J.P. (2022). Natural computing-based designing of hybrid UHMWPE composites for orthopedic implants. *Applied Sciences*, *12*, 10408. https://doi.org/10.3390/app122010408.

Asadi-Eydivand, M., Solati-Hashjin, M., Fathi, A., Padashi, M., & Abu Osman, N.A. (2016). Optimal design of a 3D-printed scaffold using intelligent evolutionary algorithms. *Applied Soft Computing*, *39*, 36–47. https://doi.org/10.1016/j.asoc.2015.11.011.

Baghaei, B., Saeb, M.R., Jafari, S.H., Khonakdar, H.A., Rezaee, B., Goodarzi, V., & Mohammadi, Y. (2017). Modeling and closed-loop control of particle size and initial burst of PLGA biodegradable nanoparticles for targeted drug delivery. *Journal of Applied Polymer Science*, *134*(33), 1–12. https://doi.org/10.1002/app.45145.

Basu, B., Gowtham, N.H., Xiao, Y., Kalidindi, S.R., & Leong, K.W. (2022). Biomaterialomics: Data science-driven pathways to develop fourth-generation biomaterials. *Acta Biomaterialia*, *143*, 1–25. https://doi.org/10.1016/j.actbio.2022.02.027.

Benkő, E., Ilič, I.G., Kristó, K., Regdon, G., Jr., Csóka, I., Pintye-Hódi, K., Srčič, S., & Sovány, T. (2022). Predicting drug release rate of implantable matrices and better understanding of the underlying mechanisms through experimental design and artificial neural network-based modelling. *Pharmaceutics*, *14*(2). https://doi.org/10.3390/pharmaceutics14020228.

Bergmann, C.P., & Stumpf, A. (2013). *Dental Ceramics: Microstructure, Properties and Degradation*. Springer Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-38224-6.

Bezdek, J.C. (1998). Computational intelligence defined – by everyone ! In O. Kaynak, L.A. Zadeh, B. Türkşen, I.J. Rudas (Eds.), *Computational Intelligence: Soft Computing and Fuzzy-Neuro Integration with Applications* (pp. 10–37). Springer Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-58930-0_2.

Bhadeshia, H.K.D.H. (1999). Neural networks in materials science. *ISIJ International*, *39*(10), 966–979. https://doi.org/10.2355/isijinternational.39.966.

Bhadeshia, H.K.D.H. (2008). Mathematical models in materials science. *Materials Science and Technology*, *24*(2), 128–136. https://doi.org/10.1179/174328407X213107.

Biswas, J.K., Dey, S., Karmakar, S.K., Roychowdhury, A., & Datta, S. (2018). Design of patient specific spinal implant (pedicle screw fixation) using fe analysis and soft computing techniques. *Current Medical Imaging Formerly Current Medical Imaging Reviews*, *16*(4), 371–382. https://doi.org/10.2174/1573405614666181018122538.

Blum, C., & Roli, A. (2003). Metaheuristics in combinatorial optimization. *ACM Computing Surveys*, *35*(3), 268–308. https://doi.org/10.1145/937503.937505.

Booker, L. (1987). Improving search in genetic algorithms. In L. Davis (Ed.), *Genetic Algorithms and Simulated Annealing* (pp. 61–73). Morgan Kaufmann Publishers.

Borjali, A., Chen, A.F., Muratoglu, O.K., Morid, M.A., & Varadarajan, K.M. (2019). *Detecting mechanical loosening of total hip replacement implant from plain radiograph using deep convolutional neural network*. Arxiv. http://arxiv.org/abs/1912.00943.

Borjali, A., Chen, A.F., Muratoglu, O.K., Morid, M.A., & Varadarajan, K.M. (2020). Detecting total hip replacement prosthesis design on plain radiographs using deep convolutional neural network. *Journal of Orthopaedic Research*, *38*(7), 1465–1471. https://doi.org/10.1002/jor.24617.

Bozzolo, G., Noebe, R.D., Abel, P.B., & Vij D.R. (2007). *Applied Computational Materials Modeling. Theory, Simulation and Experiment*. Springer New York, NY.

Bryksin, A.V., Brown, A.C., Baksh, M.M., Finn, M.G., & Barker, T.H. (2014). Learning from nature – Novel synthetic biology approaches for biomaterial design. *Acta Biomaterialia*, *10*(4), 1761–1769. https://doi.org/10.1016/j.actbio.2014.01.019.

Cha, J.-Y., Yoon, H.-I., Yeo, I.-S., Huh, K.-H., & Han, J.-S. (2021). Peri-implant bone loss measurement using a region-based convolutional neural network on dental periapical radiographs. *Journal of Clinical Medicine*, *10*(5), 1–12. https://doi.org/10.3390/jcm10051009.

Chakraborti, N. (2004). Genetic algorithms in materials design and processing. *International Materials Reviews*, *49*(3–4), 246–260. https://doi.org/10.1179/095066004225021909.

Chakraborti, N. (2016). Chapter 12. Data-driven bi-objective genetic algorithms evonn and biogp and their applications in metallurgical and materials domain. In *Computational Approaches to Materials Design: Theoretical and Practical Aspects* (pp. 346–368). IGI Global. https://doi.org/10.4018/978-1-5225-0290-6.ch012.

Chakraborti, N. (2022). *Data-Driven Evolutionary Modeling in Materials Technology*. CRC Press. https://doi.org/10.1201/9781003201045.

Chanda, S., Gupta, S., & Pratihar, D.K. (2015a). A combined neural network and genetic algorithm based approach for optimally designed femoral implant having improved primary stability. *Applied Soft Computing Journal*, *38*, 296–307. https://doi.org/10.1016/j.asoc.2015.10.020.

Chanda, S., Gupta, S., & Pratihar, D. K. (2015b). A genetic algorithm based multi-objective shape optimization scheme for cementless femoral implant. *Journal of Biomechanical Engineering*, *137*(3), 1–13. https://doi.org/10.1115/1.4029061.

Chatterjee, S., Dey, S., Majumder, S., RoyChowdhury, A., & Datta, S. (2019). Computational intelligence based design of implant for varying bone conditions. *International Journal for Numerical Methods in Biomedical Engineering*, *35*(6), 0–2. https://doi.org/10.1002/cnm.3191.

Chen, Ch.-T., & Gu, G.X. (2019). Machine learning for composite materials. *MRS Communications*, *9*(2), 556–566. https://doi.org/10.1557/mrc.2019.32.

Cheng, Y.-Ch., Jiang, Ch.P., & Lin, D.H. (2019). Finite element based optimization design for a one-piece zirconia ceramic dental implant under dynamic loading and fatigue life validation. *Structural and Multidisciplinary Optimization*, *59*(3), 835–849. https://doi.org/10.1007/s00158-018-2104-2.

Choudhury, S., Dhason, R., Roy, S., & Datta, S. (2022). Design optimization of peek hybrid composite cervical cage. *International Journal for Multiscale Computational Engineering*, *20*(4), 1–16. https://doi.org/10.1615/IntJMultCompEng.2022039152.

Chua, M.Ch.H., & Chui, Ch.-K. (2016). Optimization of patient-specific design of medical implants for manufacturing. *Procedia CIRP*, *40*, 402–406. https://doi.org/10.1016/j.procir.2016.01.078.

Cielen, D., Meysman, A., & Ali, M. (2016). *Introducing Data Science: Big Data, Machine Learning, and More, Using Python Tools*. Manning Publications.

Clinical Applications of Biomaterials (1982). *National Institute of Health Consensus Development Conference Statement*. Available from: https://consensus.nih.gov/1982/1982Biomaterials034html.htm.

Coşkun, M.İ., & Karahan, İ.H. (2018). Modeling corrosion performance of the hydroxyapatite coated CoCrMo biomaterial alloys. *Journal of Alloys and Compounds*, *745*, 840–848. https://doi.org/10.1016/j.jallcom.2018.02.253.

Datta, S. (2016). *Materials Design Using Computational Intelligence Techniques*. CRC Press. https://doi.org/10.1201/9781315373003.

Datta, S., & Banerjee, M.K. (2006). Mapping the input–output relationship in HSLA steels through expert neural network. *Materials Science and Engineering: A*, *420*(1–2), 254–264. https://doi.org/10.1016/j.msea.2006.01.037.

Datta, S., & Chattopadhyay, P.P. (2013). Soft computing techniques in advancement of structural metals. *International Materials Reviews*, *58*(8), 475–504. https://doi.org/10.1179/1743280413Y.0000000021.

Datta, S., Zhang, Q., Sultana, N., & Mahfouf, M. (2013). Optimal design of titanium alloys for prosthetic applications using a multiobjective evolutionary algorithm. *Materials and Manufacturing Processes*, *28*(7), 741–745. https://doi.org/10.1080/10426914.2013.773020.

Datta, S., Mahfouf, M., Zhang, Q., Chattopadhyay, P.P., & Sultana, N. (2016). Imprecise knowledge based design and development of titanium alloys for prosthetic applications. *Journal of the Mechanical Behavior of Biomedical Materials*, *53*, 350–365. https://doi.org/10.1016/j.jmbbm.2015.08.039.

Datta, S., Roy, S., & Davim, J.P. (2019). Optimization techniques: An overview. In S. Datta, J.P. Davim (Eds.), *Optimization in Industry. Present Practices and Future Scopes* (pp. 1–11). Springer Cham. https://doi.org/10.1007/978-3-030-01641-8_1.

Deb, K. (1995). *Optimization for Engineering Design: Algorithms and Examples*. Prentice Hall of India.

Deb, K. (2001). *Multi-objective Optimization Using Evolutionary Algorithms*. John Wiley & Sons.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, *6*(2), 182–196. https://doi.org/10.1109/4235.996017.

Deb, K., Goodman, E., Coello Coello, C.A., Klamroth, K., Miettinen, K., Mostaghim, S., & Reed, P. (Eds.) (2019). *Evolutionary Multi-Criterion Optimization. 10th International Conference, EMO 2019, East Lansing, MI, USA, March 10–13, 2019, Proceedings*. Springer Cham. https://doi.org/10.1007/978-3-030-12598-1.

Dhiman, G., & Kumar, V. (2017). Spotted hyena optimizer: A novel bio-inspired based metaheuristic technique for engineering applications. *Advances in Engineering Software*, *114*, 48–70. https://doi.org/10.1016/j.advengsoft.2017.05.014.

Ding, F., & Chen, T. (2005). Gradient based iterative algorithms for solving a class of matrix equations. *IEEE Transactions on Automatic Control*, *50*(8), 1216–1221. https://doi.org/10.1109/TAC.2005.852558.

Doghri, I., Lemoine, G., Martiny, P., Mathieu, S., Wucher, B., & Adam, L. (2021). Multiscaling-based integrated computational materials engineering: from academia to industry. *International Journal for Multiscale Computational Engineering*, *19*(4), 1–40. https://doi.org/10.1615/IntJMultCompEng.2021040073.

Domínguez-Díaz, M., & Cruz-Chavez, M.A. (2015). Scaffold architecture and properties for osteoblasts cell culture: An optimization model and application by genetic algorithm. *Materials Research Society Symposium Proceedings*, *1753*, 72–77. https://doi.org/10.1557/opl.2015.182.

Dönmez, P. (2013). Introduction to Machine Learning. *Natural Language Engineering*, *19*(2), 285–288. https://doi.org/10.1017/s1351324912000290.

Duan, Y., Gonzalez, J.A., Kulkarni, P.A., Nagy, W.W., & Griggs, J.A. (2018). Fatigue lifetime prediction of a reduced-diameter dental implant system: Numerical and experimental study. *Dental Materials*, *34*(9), 1299–1309. https://doi.org/10.1016/j.dental.2018.06.002.

Eberhart, R.C., & Shi, Y. (2007). *Computational Intelligence: Concepts to Implementations*. Elsevier/Morgan Kaufmann Publishers.

Farah, J., & El-Sheik, S.M. (2020). Fuzzy simulation of drug delivery system through valve-less micropump. *Pakistan Journal of Emerging Science and Technologies (PJEST)*, *1*(1), 1–9. http://doi.org/10.5281/zenodo.4774030.

Fatouros, D.G., Nielsen, F.S., Douroumis, D., Hadjileontiadis, L.J., & Mullertz, A. (2008). In vitro–in vivo correlations of self-emulsifying drug delivery systems combining the dynamic lipolysis model and neuro-fuzzy networks. *European Journal of Pharmaceutics and Biopharmaceutics*, *69*(3), 887–898. https://doi.org/10.1016/j.ejpb.2008.01.022.

Ganguly, S., Patra, A., Chattopadhyay, P.P., & Datta, S. (2016). New training strategies for neural networks with application to quaternary Al-Mg-Sc-Cr alloy design problems. *Applied Soft Computing Journal*, *46*, 260–266. https://doi.org/10.1016/j.asoc.2016.05.017.

Ghasemabad, E.S., Zamani, I., Tourajizadeh, H., Mirhadi, M., & Zarandi, Z.G. (2022). Design and implementation of an adaptive fuzzy sliding mode controller for drug delivery in treatment of vascular cancer tumours and its optimisation using genetic algorithm tool. *IET Systems Biology*, *16*(6), 201–219. https://doi.org/10.1049/syb2.12051.

Giri, B.K., Hakanen, J., Miettinen, K., & Chakraborti, N. (2013a). Genetic programming through bi-objective genetic algorithms with a study of a simulated moving bed process involving multiple objectives. *Applied Soft Computing*, *13*(5), 2613–2623. https://doi.org/10.1016/j.asoc.2012.11.025.

Giri, B.K., Pettersson, F., Saxén, H., & Chakraborti, N. (2013b). Genetic programming evolved through bi-objective genetic algorithms applied to a blast furnace. *Materials and Manufacturing Processes*, *28*(7), 776–782. https://doi.org/10.1080/10426914.2013.763953.

Glover, F., & Kochenberger, G.A. (Eds.). (2003). *Handbook of Metaheuristics*. Springer New York, NY. https://doi.org/10.1007/b101874.

Goldberg, D.E. (2002). *Genetic Algorithms in Search, Optimization, and Machine Learning*. Pearson-Education.

Gronau, G., Krishnaji, S.T., Kinahan, M.E., Giesa, T., Wong, J.Y., Kaplan, D.L., & Buehler, M.J. (2012). A review of combined experimental and computational procedures for assessing biopolymer structure-process-property relationships. *Biomaterials*, *33*(33), 8240–8255. https://doi.org/10.1016/j.biomaterials.2012.06.054.

Guessasma, S., & Bassir, D.H. (2010). Identification of mechanical properties of biopolymer composites sensitive to interface effect using hybrid approach. *Mechanics of Materials*, *42*(3), 344–353. https://doi.org/10.1016/j.mechmat.2009.12.001.

Gurney, K. (2018). *An Introduction to Neural Networks*. CRC Press.

Haghdoost, F., Razbin, M., Bahrami, H., Barzin, J., & Ghaee, A. (2022). Modeling and optimization of the core-shell nanofibrous composite mat as a scaffold via hybrid models. *Journal of Industrial Textiles*, *52*, 152808372211124. https://doi.org/10.1177/15280837221112406.

Halim, A.H., Ismail, I., & Das, S. (2021). Performance assessment of the metaheuristic optimization algorithms: an exhaustive review. *Artificial Intelligence Review*, *54*(3), 2323–2409. https://doi.org/10.1007/s10462-020-09906-6.

Hamidian, A.H., Esfandeh, S., Zhang, Y., & Yang, M. (2019). Simulation and optimization of nanomaterials application for heavy metal removal from aqueous solutions. *Inorganic and Nano-Metal Chemistry*, *49*(7), 217–230. https://doi.org/10.1080/24701556.2019.1653321.

Han, R., Yang, Y., Li, X., & Ouyang, D. (2018). Predicting oral disintegrating tablet formulations by neural network techniques. *Asian Journal of Pharmaceutical Sciences*, *13*(4), 336–342. https://doi.org/10.1016/j.ajps.2018.01.003.

Hariharan, K., Nguyen, N.-T., Chakraborti, N., Lee, M.-G., & Barlat, F. (2014). Multi-objective genetic algorithm to optimize variable drawbead geometry for tailor welded blanks made of dissimilar steels. *Steel Research International*, *85*(12), 1597–1607. https://doi.org/10.1002/srin.201300471.

He, S. (2021). Who is liable for the UBER self-driving crash? Analysis of the liability allocation and the regulatory model for autonomous vehicles. In S. Van Uytsel, D. Vasconcellos Vargas (Eds.), *Autonomous Vehicles. Business, Technology and Law* (pp. 93–111). https://doi.org/10.1007/978-981-15-9255-3_5.

Hebels, D.G.A.J., Carlier, A., Coonen, M.L.J., Theunissen, D.H., & de Boer, J. (2017). cBiT: A transcriptomics database for innovative biomaterial engineering. *Biomaterials*, *149*, 88–97. https://doi.org/10.1016/j.biomaterials.2017.10.008.

Heljak, M.K., Święszkowski, W., Lam, C.X.F., Hutmacher, D.W., & Kurzydłowski, K.J. (2012). Evolutionary design of bone scaffolds with reference to material selection. *International Journal for Numerical Methods in Biomedical Engineering*, *28*(6–7), 789–800. https://doi.org/10.1002/cnm.2487.

Heljak, M.K., Kurzydlowski, K.J., & Swieszkowski, W. (2017). Computer aided design of architecture of degradable tissue engineering scaffolds. *Computer Methods in Biomechanics and Biomedical Engineering*, *20*(15), 1623–1632. https://doi.org/10.1080/10255842.2017.1399263.

Jajarmi, E., Sajjadi, S.A., & Mohebbi, J. (2019). Predicting the relative density and hardness of 3YPSZ/316L composites using adaptive neuro-fuzzy inference system and support vector regression models. *Measurement: Journal of the International Measurement Confederation*, *145*, 472–479. https://doi.org/10.1016/j.measurement.2019.05.108.

Janssens, K., Raabe, D., Kozeschnik, E., Miodownik, M., & Nestler, B. (2010). *Computational Materials Engineering: An Introduction to Microstructure Evolution*. Academic Press.

Jeong, C.G., Francisco, A.T., Niu, Z., Mancino, R.L., Craig, S.L., & Setton, L.A. (2014). Screening of hyaluronic acid-poly(ethylene glycol) composite hydrogels to support intervertebral disc cell biosynthesis using artificial neural network analysis. *Acta Biomaterialia*, *10*(8), 3421–3430. https://doi.org/10.1016/j.actbio.2014.05.012.

Jha, R., & Dulikravich, G.S. (2021). Discovery of new Ti-based alloys aimed at avoiding/minimizing formation of α″ and ω-phase using. *Metals*, *11*(1), 15. https://doi.org/10.3390/met11010015.

Joorabloo, A., Khorasani, M.T., Adeli, H., Mansoori-Moghadam, Z., & Moghaddam, A. (2019). Fabrication of heparinized nano ZnO/poly(vinylalcohol)/carboxymethyl cellulose bionanocomposite hydrogels using artificial neural network for wound dressing application. *Journal of Industrial and Engineering Chemistry*, *70*, 253–263. https://doi.org/10.1016/j.jiec.2018.10.022.

Kalidindi, S.R., & De Graef, M. (2015). Materials Data Science: current status and future outlook. *Annual Review of Materials Research*, *45*, 171–193. https://doi.org/10.1146/annurev-matsci-070214-020844.

Karimi, M.A., Pourhakkak, P., Adabi, M., Firoozi, S., Adabi, M., & Naghibzadeh, M. (2015). Using an artificial neural network for the evaluation of the parameters controlling PVA/chitosan electrospun nanofibers diameter. *E-Polymers*, *15*(2), 127–138. https://doi.org/10.1515/epoly-2014-0198.

Kartal, F., & Özveren, U. (2021). An improved machine learning approach to estimate hemicellulose, cellulose, and lignin in biomass. *Carbohydrate Polymer Technologies and Applications*, *2*, 100148. https://doi.org/10.1016/j.carpta.2021.100148.

Kazemi, M., Ahangarani, S., Esmailian, M., & Shanaghi, A. (2022). Investigating the corrosion performance of Ti-6Al-4V biomaterial alloy with hydroxyapatite coating by artificial neural network. *Materials Science and Engineering: B*, *278*, 115644. https://doi.org/10.1016/j.mseb.2022.115644.

Khalili, S., Khorasani, S.N., Saadatkish, N., & Khoshakhlagh, K. (2016). Characterization of gelatin/cellulose acetate nanofibrous scaffolds: Prediction and optimization by response surface methodology and artificial neural networks. *Polymer Science – Series A*, *58*(3), 399–408. https://doi.org/10.1134/S0965545X16030093.

Khanlou, H.M., Ang, B.C., & Barzani, M.M. (2016). Prediction, modeling and characterization of surface texturing by sulfuric etchant on non-toxic titanium bio-material using artificial neural networks and fuzzy logic systems. *Science and Engineering of Composite Materials*, *23*(4), 423–433. https://doi.org/10.1515/secm-2014-0230.

Kim, J.-E., Nam, N.-E., Shim, J.-S., Jung, Y.-H., Cho, B.-H., & Hwang, J.J. (2020). Transfer learning via deep neural networks for implant fixture system classification using periapical radiographs. *Journal of Clinical Medicine*, *9*(4). https://doi.org/10.3390/jcm9041117.

Kondiah, P.J., Kondiah, P.P.D., Choonara, Y.E., Marimuthu, T., & Pillay, V. (2020). A 3D bioprinted pseudo-bone drug delivery scaffold for bone tissue engineering. *Pharmaceutics*, *12*(2). https://doi.org/10.3390/pharmaceutics12020166.

Kumar, A., & Raj, R. (2022). Design of a fractional order two layer fuzzy logic controller for drug delivery to regulate blood pressure. *Biomedical Signal Processing and Control*, *78*, 104024. https://doi.org/10.1016/j.bspc.2022.104024.

Kumar, R., Chohan, J.S., Singh, S., Sharma, S., Singh, Y., & Rajkumar, S. (2022). Implementation of taguchi and genetic algorithm techniques for prediction of optimal part dimensions for polymeric biocomposites in fused deposition modeling. *International Journal of Biomaterials*, *2022*, 1–7. https://doi.org/10.1155/2022/4541450.

Kumari, S., Tiyyagura, H.R., Douglas, T.E.L., Mohammed, E.A.A., Adriaens, A., Fuchs-Godec, R., Mohan, M.K., & Skirtach, A.G. (2018). ANN prediction of corrosion behaviour of uncoated and biopolymers coated cp-Titanium substrates. *Materials and Design*, *157*, 35–51. https://doi.org/10.1016/j.matdes.2018.07.005.

Kurt, H.I., & Oduncuoglu, M. (2015). Application of a neural network model for prediction of wear properties of ultrahigh molecular weight polyethylene composites. *International Journal of Polymer Science*, *2015*, 1–11. https://doi.org/10.1155/2015/315710.

Kwak, Y., Nguyen, V.-H., Hériveaux, Y., Belanger, P., Park, J., & Haïat, G. (2021). Ultrasonic assessment of osseointegration phenomena at the bone-implant interface using convolutional neural network. *The Journal of the Acoustical Society of America*, *149*(6), 4337–4347. https://doi.org/10.1121/10.0005272.

Kwaria, R.J., Mondarte, E.A.Q., Tahara, H., Chang, R., & Hayashi, T. (2020). Data-driven prediction of protein adsorption on self-assembled monolayers toward material screening and design. *ACS Biomaterials Science and Engineering*, *6*(9), 4949–4956. https://doi.org/10.1021/acsbiomaterials.0c01008.

Lahiri, D., Nag, M., Sarkar, T., Dutta, B., & Ray, R.R. (2021). Antibiofilm activity of α-amylase from bacillus subtilis and prediction of the optimized conditions for biofilm removal by Response Surface Methodology (RSM) and Artificial Neural Network (ANN). *Applied Biochemistry and Biotechnology*, *193*(6), 1853–1872. https://doi.org/10.1007/s12010-021-03509-9.

Langley, P. (2011). The changing science of machine learning. *Machine Learning*, *82*(3), 275–279. https://doi.org/10.1007/s10994-011-5242-y.

Le, T.C., & Tran, N. (2019). Using machine learning to predict the self-assembled nanostructures of monoolein and phytantriol as a function of temperature and fatty acid additives for effective lipid-based delivery systems. *ACS Applied Nano Materials*, *2*(3), 1637–1647. https://doi.org/10.1021/acsanm.9b00075.

Lee, J.H., & Jeong, S.-N. (2020). Efficacy of deep convolutional neural network algorithm for the identification and classification of dental implant systems, using panoramic and periapical radiographs: A pilot study. *Medicine*, *99*(26), e20787. https://doi.org/10.1097/MD.0000000000020787.

Li, X., Liang, H., Tang, X., Wu, J., & Wang, J. (2022). A fuzzy analysis for porous bioceramic-magnetite nanoparticles-zirconia scaffold prepared by space holder technique with poly vinyl pyrrolidone (PVP) coating: Investigation of mechanical and biological properties. *Ceramics International*, *48*(11), 16221–16231. https://doi.org/10.1016/j.ceramint.2022.02.170.

Liu, Z.K., Chen, L.-Q., & Rajan, K. (2006). Linking length scales via materials informatics. *JOM*, *58*(11), 42–50. https://doi.org/10.1007/s11837-006-0226-2.

Madi, K., Tozzi, G., Zhang, Q. H., Tong, J., Cossey, A., Au, A., Hollis, D., & Hild, F. (2013). Computation of full-field displacements in a scaffold implant using digital volume correlation and finite element analysis. *Medical Engineering & Physics*, *35*(9), 1298–1312. https://doi.org/10.1016/j.medengphy.2013.02.001.

Maeda, C., Kobashi, S., Shibanuma, N., Kondo, K., & Hata, Y. (2005). 3D strain detection of a support implant for an artificial hip joint using finite element method and genetic algorithm. *Digital Image Computing: Techniques and Applications (DICTA'05)*, 23–23. https://doi.org/10.1109/DICTA.2005.2.

Mamdani (1977). Application of fuzzy logic to approximate reasoning using linguistic synthesis. *IEEE Transactions on Computers*, *C-26*(12), 1182–1191. https://doi.org/10.1109/TC.1977.1674779.

Manai, Y., Benrejeb, M., & Borne, P. (2011). New approach of stability for time-delay takagi-sugeno fuzzy system based on fuzzy weighting-dependent lyapunov functionals. *Applied Mathematics*, *2*(11), 1339–1345. https://doi.org/10.4236/am.2011.211187.

Manda, A., Walker, R.B., & Khamanga, S.M.M. (2019). An artificial neural network approach to predict the effects of formulation and process variables on prednisone release from a multipartite system. *Pharmaceutics*, *11*(3), 1–19. https://doi.org/10.3390/pharmaceutics11030109.

Mandal, S., Sivaprasad, P.V., Venugopal, S., & Murthy, K.P.N. (2009). Artificial neural network modeling to evaluate and predict the deformation behavior of stainless steel type AISI 304L during hot torsion. *Applied Soft Computing*, *9*(1), 237–244. https://doi.org/10.1016/j.asoc.2008.03.016.

McDowell, D.L., Panchal, J.H., Choi, H.-J., Seepersad, C.C., Allen, J.K., & Mistree, F. (2010). *Integrated Design of Multiscale, Multifunctional Materials and Products*. Elsevier.

Michalewicz, Z., & Fogel, D.B. (2004). *How to Solve It: Modern Heuristics* (2 ed.). Springer Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-07807-5.

Moayeri S.R., Khalili, M., & Nazari, M. (2016). A hybrid method to predict success of dental implants. *International Journal of Advanced Computer Science and Applications*, *7*(5), 3–8. https://doi.org/10.14569/ijacsa.2016.070501.

Mueller, T., Kusne, A.G., & Ramprasad, R. (2016). Machine learning in materials science: recent progress and emerging applications. *Reviews in Computational Chemistry*, *29*, 186–273. https://doi.org/10.1002/9781119148739.ch4.

Mukherjee, M., & Singh, S.B. (2009). Artificial neural network: some applications in physical metallurgy of steels. *Materials and Manufacturing Processes*, *24*(2), 198–208. https://doi.org/10.1080/10426910802612304.

Muñiz Castro, B., Elbadawi, M., Ong, J.J., Pollard, T., Song, Z., Gaisford, S., Pérez, G., Basit, A.W., Cabalar, P., & Goyanes, A. (2021). Machine learning predicts 3D printing performance of over 900 drug delivery systems. *Journal of Controlled Release*, *337*, 530–545. https://doi.org/10.1016/j.jconrel.2021.07.046.

Murphy, M., Killen, C., Burnham, R., Sarvari, F., Wu, K., & Brown, N. (2021). Artificial intelligence accurately identifies total hip arthroplasty implants: a tool for revision surgery. *HIP International*, 32(6), 766–770. https://doi.org/10.1177/1120700020987526.

Narayana, P.L., Maurya, A.K., Wang, X.-S., Harsha, M.R., Srikanth, O., Alnuaim, A.A., Hatamleh, W.A., Hatamleh, A.A., Cho, K.K., Paturi, U.M.R., & Reddy, N.S. (2021). Artificial neural networks modeling for lead removal from aqueous solutions using iron oxide nanocomposites from bio-waste mass. *Environmental Research*, *199*, 111370. https://doi.org/10.1016/j.envres.2021.111370.

Nazari, M., Babaei, N., & Nazari, M. (2021). Nonlinear SDRE based adaptive fuzzy control approach for age-specific drug delivery in mixed chemotherapy and immunotherapy. *Biomedical Signal Processing and Control*, *68*, 102687. https://doi.org/10.1016/j.bspc.2021.102687.

Nighojkar, A., Zimmermann, K., Ateia, M., Barbeau, B., Mohseni, M., Krishnamurthy, S., Dixit, F., & Kandasubramanian, B. (2022). Application of neural network in metal adsorption using biomaterials (BMs): a review. *Environmental Science: Advances*. https://doi.org/10.1039/d2va00200k.

Nilsson, N.J. (2005). Introduction to Machine Learning – an Early Draft of a Proposed Textbook. https://ai.stanford.edu/~nilsson/MLBOOK.pdf.

Noori Banu, P.S., & Devaki Rani, S. (2018). Artificial neural network based optimization of prerequisite properties for the design of biocompatible titanium alloys. *Computational Materials Science*, *149*, 259–266. https://doi.org/10.1016/j.commatsci.2018.03.039.

Olson, G.B. (1997). Computational design of hierarchically structured materials. *Science*, *277*(5330), 1237–1242. https://doi.org/10.1126/science.277.5330.1237.

Olson, G.B. (2000). Designing a new material world. *Science*, *288*(5468), 993–998. https://doi.org/10.1126/science.288.5468.993.

Özkal, F.M., Cakir, F., & Sensoz, E. (2020). Schematization of cannulated screw fixations in femoral neck fractures using genetic algorithm and finite element method. *Journal of Medical and Biological Engineering*, *40*(5), 673–687. https://doi.org/10.1007/s40846-020-00528-5.

Pablo, J.J., de, Jones, B., Kovacs, C.L., Ozolins, V., & Ramirez, A.P. (2014). The Materials Genome Initiative, the interplay of experiment, theory and computation. *Current Opinion in Solid State and Materials Science*, *18*(2), 99–117. https://doi.org/10.1016/j.cossms.2014.02.003.

Pablo, J.J., de, Jackson, N.E., Webb, M.A., Chen, L.-Q., Moore, J.E., Morgan, D., Jacobs, R., Pollock, T., Schlom, D.G., Toberer, E.S., Analytis, J., Dabo, I., DeLongchamp, D.M., Fiete, G.A., Grason, G.M., Hautier, G., Mo, Y., Rajan, K., Reed, E.J., Rodriguez, E., Stevanovic, V., Suntivich, J., Thornton, K., & Zhao, J.-Ch. (2019). New frontiers for the materials genome initiative. *npj Computational Materials*, *5*(1), 41. https://doi.org/10.1038/s41524-019-0173-4.

Parisi, L. (2014). Neural networks for distinguishing the performance of two hip joint implants on the basis of hip implant side and ground reaction force. *International Journal of Medical, Health, Pharmaceutical and Biomedical Engineering*, *8*(10), 731–735. https://doi.org/10.13140/2.1.4563.6166.

Park, J.B., & Bronzino, J.D. (2003). *Biomaterials: Principles and Applications*. CRC Press.

Paskiabi, F.A., Mirzaei, E., Amani, A., Shokrgozar, M.A., Saber, R., & Faridi-Majidi, R. (2015). Optimizing parameters on alignment of PCL/PGA nanofibrous scaffold: An artificial neural networks approach. *International Journal of Biological Macromolecules*, *81*, 1089–1097. https://doi.org/10.1016/j.ijbiomac.2014.10.040.

Paz, R., & Monzón, M.D. (2019). Optimization methodology for the material assignation in bioprinted scaffolds to achieve the desired stiffness over time. *International Journal for Numerical Methods in Biomedical Engineering*, *35*(10), 1–17. https://doi.org/10.1002/cnm.3248.

Pettersson, F., Chakraborti, N., & Saxén, H. (2007). A genetic algorithms based multi-objective neural net applied to noisy blast furnace data. *Applied Soft Computing*, *7*(1), 387–397. https://doi.org/10.1016/j.asoc.2005.09.001.

Prajapati, D.K., & Tiwari, M. (2017). Use of artificial neural network (ANN) to determining surface parameters, friction and wear during pin-on-disc tribotesting. *Key Engineering Materials*, *739*, 87–95. https://doi.org/10.4028/www.scientific.net/kem.739.87.

Prakash, C., Kansal, H.K., Pabla, B.S., & Puri, S. (2016). To optimize the surface roughness and microhardness of β-Ti alloy in PMEDM process using Non-dominated Sorting Genetic Algorithm-II. *2015 2nd International Conference on Recent Advances in Engineering and Computational Sciences, RAECS 2015*. https://doi.org/10.1109/RAECS.2015.7453288.

Quan, G.-z., Pu, S.-a., Zhan, Z.-y., Zou, Z.-y., Liu, Y-y., & Xia, Y.-f. (2015). Modelling of the hot flow behaviors for Ti-13Nb-13Zr alloy by BP-ANN model and its application. *International Journal of Precision Engineering and Manufacturing*, *16*(10), 2129–2137. https://doi.org/10.1007/s12541-015-0275-y.

Raabe, D. (1998). *Computational Materials Science: The simulation of materials and microstructures and properties*. Wiley-VCH.

Rafienia, M., Amiri, M., Janmaleki, M., & Sadeghian, A. (2010). Application of artificial neural networks in controlled drug delivery systems. *Applied Artificial Intelligence*, *24*(8), 807–820. https://doi.org/10.1080/08839514.2010.508606.

Rajan, K. (2005). Materials informatics. *Materials Today*, *8*(10), 38–45. https://doi.org/10.1016/S1369-7021(05)71123-8.

Ratner, B.D., & Hoffman, A.S., Shoen, F.J., & Lemons, J.E. (Eds.) (1996). *Biomaterials Science: An Introduction to Materials in Medicine*. Academic Press.

Reddy, B.S., In, K.H., Panigrahi, B.B., Paturi, U.M.R., Cho, K.K., & Reddy, N.S. (2021). Modeling tensile strength and suture retention of polycaprolactone electrospun nanofibrous scaffolds by artificial neural networks. *Materials Today Communications*, *26*, 102115. https://doi.org/10.1016/j.mtcomm.2021.102115.

Rezende, R., Rezende, M., Bártolo, P., Mendes, A., & Filho, R.M. (2009). Optimization of scaffolds in alginate for biofabrication by genetic algorithms. In R.M. de Brito Alves, C.A.O. do Nascimento, E. Chalbaud Biscaia Jr. (Eds.), *10th International Symposium on Process Systems Engineering: Part A*. Elsevier. https://doi.org/10.1016/S1570-7946(09)70713-8.

Rouhollahi, A., Ilegbusi, O., & Foroosh, H. (2021). Segmentation and pore structure estimation in SEM images of tissue engineering scaffolds using genetic algorithm. *Annals of Biomedical Engineering*, *49*(3), 1033–1045. https://doi.org/10.1007/s10439-020-02638-2.

Roy, S., & Chakraborti, N. (2022). Novel strategies for data-driven evolutionary optimization. In P. Tuovinen, T. Periaux, J. Neittaanmäki (Eds.), *Computational Sciences and Artificial Intelligence in Industry. New Digital Technologies for Solving Future Societal and Economical Challenges* (pp. 11–25). Springer Cham. https://doi.org/10.1007/978-3-030-70787-3_2.

Roy, S., Dey, S., Khutia, N., Roy Chowdhury, A., & Datta, S. (2018). Design of patient specific dental implant using FE analysis and computational intelligence techniques. *Applied Soft Computing*, *65*, 272–279. https://doi.org/10.1016/j.asoc.2018.01.025.

Roy, S., Saini, B.S., Chakrabarti, D., & Chakraborti, N. (2020). Mechanical properties of micro-alloyed steels studied using a evolutionary deep neural network. *Materials and Manufacturing Processes*, *35*(6), 611–624. https://doi.org/10.1080/10426914.2019.1660786.

Russell, S., & Norvig, P. (2021). *Artificial Intelligence. A Modern Approach* (4 Ed.). Pearson.

Russo, G., Reche, P., Pennisi, M., & Pappalardo, F. (2020). The combination of artificial intelligence and systems biology for intelligent vaccine design. *Expert Opinion on Drug Discovery*, *15*(11), 1267–1281. https://doi.org/10.1080/17460441.2020.1791076.

Sadollah, A., & Bahreininejad, A. (2011). Optimum gradient material for a functionally graded dental implant using metaheuristic algorithms. *Journal of the Mechanical Behavior of Biomedical Materials*, *4*(7), 1384–1395. https://doi.org/10.1016/j.jmbbm.2011.05.009.

Sai, T., Pathak, V.K., & Srivastava, A.K. (2020). Modeling and optimization of fused deposition modeling (FDM) process through printing PLA implants using adaptive neuro-fuzzy inference system (ANFIS) model and whale optimization algorithm. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *42*(12), 1–19. https://doi.org/10.1007/s40430-020-02699-3.

Sanghvi, N., Vora, D., Charaya, E., Patel, J., & Sharma, S. (2021). An approach for material selection for bone staple (an orthopaedic implant) using GRA and Fuzzy logic. *Materials Today: Proceedings*, *44*(1), 1300–1306. https://doi.org/10.1016/j.matpr.2020.11.331.

Schmidt, J., Marques, M.R.G., Botti, S., & Marques, M.A.L. (2019). Recent advances and applications of machine learning in solid-state materials science. *npj Computational Materials*, *5*(1), 83. https://doi.org/10.1038/s41524-019-0221-0.

Semnani, D. (2014). A novel model of optimum nanofiber distribution in nanofiber scaffold structure by genetic algorithm method. *Journal of Experimental Nanoscience*, *9*(9), 966–981. https://doi.org/10.1080/17458080.2012.752583.

Shabbir, J., & Anwer, T. (2018). *Artificial intelligence and its role in near future*. Arxiv. https://doi.org/10.48550/arXiv.1804.01396.

Shalev-Shwartz, S., & Ben-David, S. (2013). *Understanding Machine Learning: From Theory to Algorithms*. Cambridge University Press. https://doi.org/10.1017/CBO9781107298019.

Shera, S.S., Sahu, S., & Banik, R.M. (2018). Preparation of drug eluting natural composite scaffold using response surface methodology and artificial neural network approach. *Tissue Engineering and Regenerative Medicine*, *15*(2), 131–143. https://doi.org/10.1007/s13770-017-0100-z.

Sidhu, S.S., Singh, H., & Gepreel, M.A.H. (2021). A review on alloy design, biological response, and strengthening of β-titanium alloys as biomaterials. *Materials Science and Engineering: C*, *121*, 111661. https://doi.org/10.1016/j.msec.2020.111661.

Sudhakar, K.V., & Haque, M.E. (2013). Artificial neural network model: Prediction of mechanical properties in beta-titanium biomaterial. *Applied Mechanics and Materials*, *367*, 40–44. https://doi.org/10.4028/www.scientific.net/AMM.367.40.

Sugeno, M. (1985). *Industrial applications of fuzzy control*. Elsevier Science.

Suh, C., Rajan, K., Vogel, B.M., Narasimhan, B., & Mallapragada, S.K. (2006). Chapter 5. Informatics methods for combinatorial materials science. In B. Narasimhan, S.K. Mallapragada, M.D. Porter (Eds.), *Combinatorial Materials Science* (pp. 109–119). John Wiley & Sons. https://doi.org/10.1002/9780470140475.ch5.

Sukegawa, S., Yoshii, K., Hara, T., Yamashita, K., Nakano, K., Yamamoto, N., Nagatsuka, H., & Furuki, Y. (2020). Deep neural networks for dental implant system classification. *Biomolecules*, *10*(7), 984. https://doi.org/10.3390/biom10070984.

Sultana, N., Sikdar (Dey), S., Chattopadhyay, P. P., & Datta, S. (2014). Informatics based design of prosthetic Ti alloys. *Materials Technology*, *29*(sup1, Part B1), B69–B75. https://doi.org/10.1179/1753555713y.0000000103.

Sundman, B., Dupin, N., & Hallstedt, B. (2021). Algorithms useful for calculating multi-component equilibria, phase diagrams and other kinds of diagrams. *Calphad*, *75*, 102330. https://doi.org/10.1016/j.calphad.2021.102330.

Szarek, A., Korytkowski, M., Rutkowski, L., Scherer, R., & Szyprowski, J. (2012). Application of neural networks in assessing changes around implant after total hip arthroplasty. In L. Rutkowski, M. Korytkowski, R. Scherer, R. Tadeusiewicz, L.A. Zadeh, J.M. Zurada (Eds.), *International Conference on Artificial Intelligence and Soft Computing. ICAISC 2012: Artificial Intelligence and Soft Computing* (pp. 335–340). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-29350-4_40.

Tao, W.M., & Zhang, M. (2005). A genetic algorithm-based area coverage approach for controlled drug delivery using microrobots. *Nanomedicine: Nanotechnology, Biology, and Medicine*, *1*(1), 91–100. https://doi.org/10.1016/j.nano.2004.11.006.

Thomas, K.A., Dey, S., Sultana, N., Sarkar, K., & Datta, S. (2020). Design of Ti composite with bioactive surface for dental implant. *Materials and Manufacturing Processes*, *35*(6), 643–651. https://doi.org/10.1080/10426914.2020.1711927.

Vasilevich, A., Carlier, A., Winkler, D.A., Singh, S., & Boer, J., de (2020). Evolutionary design of optimal surface topographies for biomaterials. *Scientific Reports*, *10*(1), 1–10. https://doi.org/10.1038/s41598-020-78777-2.

Vatankhah, E., Semnani, D., Prabhakaran, M. P., Tadayon, M., Razavi, S., & Ramakrishna, S. (2014). Artificial neural network for modeling the elastic modulus of electrospun polycaprolactone/gelatin scaffolds. *Acta Biomaterialia*, *10*(2), 709–721. https://doi.org/10.1016/j.actbio.2013.09.015.

Villaseñor-Cavazos, F.J., Torres-Valladares, D., & Lozano, O. (2022). Modeling and optimization of nanovector drug delivery systems: exploring the most efficient algorithms. *Journal of Nanoparticle Research*, *24*(6), 1–19. https://doi.org/10.1007/s11051-022-05499-z.

Vinoth, A., & Datta, S. (2020a). Optimization of mechanical characteristics of UHMWPE composites using computational intelligence. In R. Prakash, R. Suresh Kumar, A. Nagesha, G. Sasikala, A. Bhaduri (Eds.), *Structural Integrity Assessment. Proceedings of ICONS 2018* (pp. 211–220). Springer Singapore. https://doi.org/10.1007/978-981-13-8767-8_17.

Vinoth, A., & Datta, S. (2020b). Design of the ultrahigh molecular weight polyethylene composites with multiple nanoparticles: An artificial intelligence approach. *Journal of Composite Materials*, *54*(2), 179–192. https://doi.org/10.1177/0021998319859924.

Vinoth, A., Dey, S., & Datta, S. (2021a). Designing UHMWPE hybrid composites using machine learning and metaheuristic algorithms. *Composite Structures*, *267*, 113898. https://doi.org/10.1016/j.compstruct.2021.113898.

Vinoth, A., Nirmal, K. N., Khedar, R., & Datta, S. (2021b). Optimizing the tribological properties of UHMWPE nanocomposites – an artificial intelligence based approach. In E. Akinlabi, P. Ramkumar, M. Selvaraj (Eds.), *Trends in Mechanical and Biomedical Design. Select Proceedings of ICMechD 2019* (pp. 831–843) Springer Singapore. https://doi.org/10.1007/978-981-15-4488-0_70.

Vu, G.T.T., Phan, N.T., Nguyen, H.T., Nguyen, H.C., Hai Tran, Y.T., Pham, T.B., Nguyen, L.T., & Nguyen, H.D. (2020). Application of the artificial neural network to optimize the formulation of self-nanoemulsifying drug delivery system containing rosuvastatin. *Journal of Applied Pharmaceutical Science*, *10*(9), 1–11. https://doi.org/10.7324/JAPS.2020.10901.

Williams, D.F. (1999). *The Williams Dictionary of Biomaterials*. Liverpool University Press. https://doi.org/10.5949/UPO9781846314438.

Willumeit, R., Feyerabend, F., & Huber, N. (2013). Magnesium degradation as determined by artificial neural networks. *Acta Biomaterialia*, *9*(10), 8722–8729. https://doi.org/10.1016/j.actbio.2013.02.042.

Wu, C.-T., Chang, H.-T., Wu, C.-Y., Chen, S.-W., Huang, S.-Y., Huang, M., Pan, Y.-T., Bradbury, P., Chou, J., & Yen, H.-W. (2020). Machine learning recommends affordable new Ti alloy with bone-like modulus. *Materials Today*, *34*, 41–50. https://doi.org/10.1016/j.mattod.2019.08.008.

Wu, C.-T., Lin, P.-H., Huang, S.-Y., Tseng, Y.-J., Chang, H.-T., Li, S.-Y., & Yen, H.-W. (2022). Revisiting alloy design of low-modulus biomedical β-Ti alloys using an artificial neural network. *Materialia*, *21*, 101313. https://doi.org/10.1016/j.mtla.2021.101313.

Yaghoubzadeh-Bavandpour, A., Bozorg-Haddad, O., Zolghadr-Asli, B., & Singh, V.P. (2022). Computational intelligence: an introduction. In O. Bozorg-Haddad, B. Zolghadr-Asli (Eds.), *Computational Intelligence for Water and Environmental Sciences* (pp. 411–427). Springer Singapore. https://doi.org/10.1007/978-981-19-2519-1_19.

Yang, F., Li, Z., Wang, Q., Jiang, B., Yan, B., Zhang, P., Xu, W., Dong, C., & Liaw, P.K. (2020). Cluster-formula-embedded machine learning for design of multicomponent β-Ti alloys with low Young's modulus. *npj Computational Materials*, *6*(1), 101. https://doi.org/10.1038/s41524-020-00372-w.

Yaszemski, M.J., Trantolo, D.J., Lewandrowski, K.-U., Hasirci, V., Altobelli, D.E., & Wise, D.L. (Eds.) (2004). *Biomaterials in Orthopedics*. Marcel Dekker.

Yi Wang, W., Li, J., Liu, W., & Liu, Z.-K. (2019). Integrated computational materials engineering for advanced materials: A brief review. *Computational Materials Science*, *158*, 42–48. https://doi.org/10.1016/j.commatsci.2018.11.001.

You, W.S., Casebier, J., Mandich, J., & Balasubramanian, R. (2021). Genetic algorithm-based optimization for the geometric design of a novel orthopedic implant. *IEEE Transactions on Biomedical Engineering*, *68*(12), 3620–3627. https://doi.org/10.1109/TBME.2021.3080226.

Younesi, M., Bahrololoom, M.E., & Ahmadzadeh, M. (2010). Prediction of wear behaviors of nickel free stainless steel-hydroxyapatite bio-composites using artificial neural network. *Computational Materials Science*, *47*(3), 645–654. https://doi.org/10.1016/j.commatsci.2009.09.019.

Zadeh, L.A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X.

Zadeh, L.A. (1988). Fuzzy logic. *Computer*, *21*(4), 83–93. https://doi.org/10.1109/2.53.

Zaw, K., Liu, G.R., Deng, B., & Tan, K.B.C. (2009). Rapid identification of elastic modulus of the interface tissue on dental implants surfaces using reduced-basis method and a neural network. *Journal of Biomechanics*, *42*(5), 634–641. https://doi.org/10.1016/j.jbiomech.2008.12.001.

Zedeh, L.A. (1989). Knowledge representation in fuzzy logic. *IEEE Transactions on Knowledge and Data Engineering*, *1*(1), 89–100. https://doi.org/10.1109/69.43406.

Zheng, S., Xiong, J., Wang, L., Zhai, D., Xu, Y., & Lin, F. (2021). e-Graphene: A computational platform for the prediction of graphene-based drug delivery system by quantum genetic algorithm and cascade protocol. *Frontiers in Chemistry*, *9*, 1–15. https://doi.org/10.3389/fchem.2021.664355.

Zhou, W., Chen, F., Zong, Y., Zhao, D., Jie, B., Wang, Z., Huang, C., & Ng, E.Y.K. (2019). Automatic detection approach for bioresorbable vascular scaffolds using a u-shaped convolutional neural network. *IEEE Access*, *7*, 94424–94430. https://doi.org/10.1109/ACCESS.2019.2926523.